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Parameterized Macromodeling and Model Order Reduction for High-Speed Interconnects

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Outline

Introduction

Parameterized Macromodels

New interpolation with scaling-shifting coefficients

Numerical examples
- Spiral inductor
- PCB

Conclusions

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Introduction

Parameterized Macromodels

New interpolation with scaling-shifting coefficients

Numerical examples

- **Spiral inductor**
- **PCB**

Conclusions

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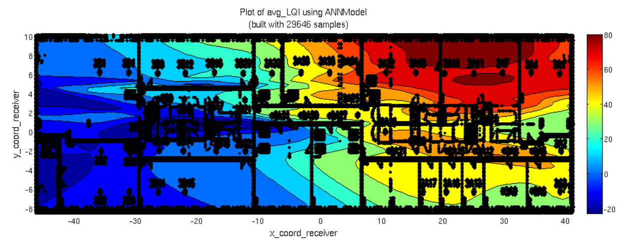
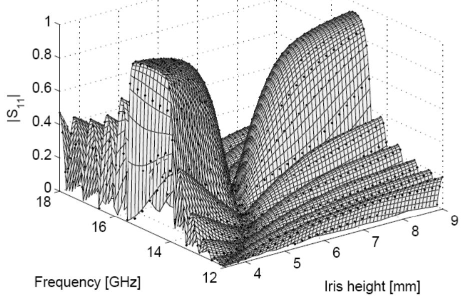
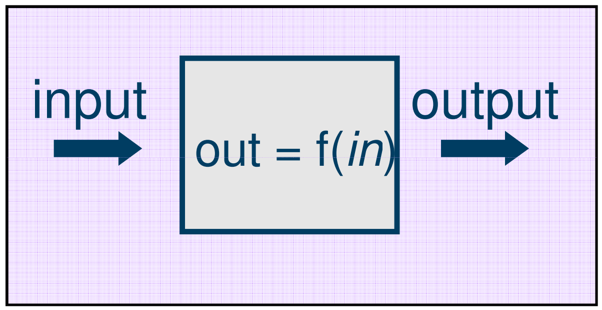
telecom

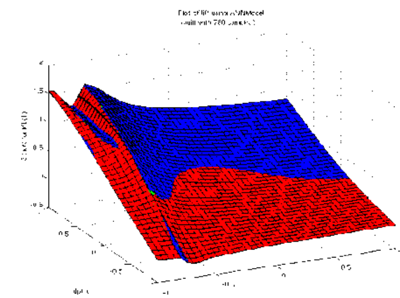


electronics



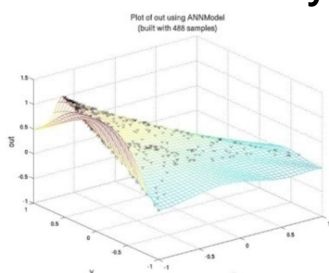


fluid dynamics

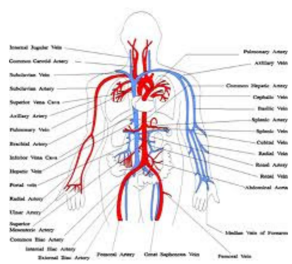


automotive

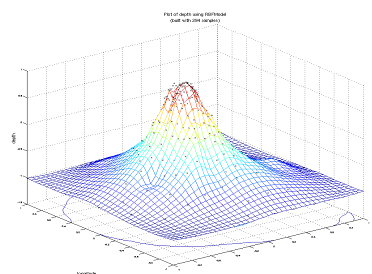
chemistry



biomodeling



geology



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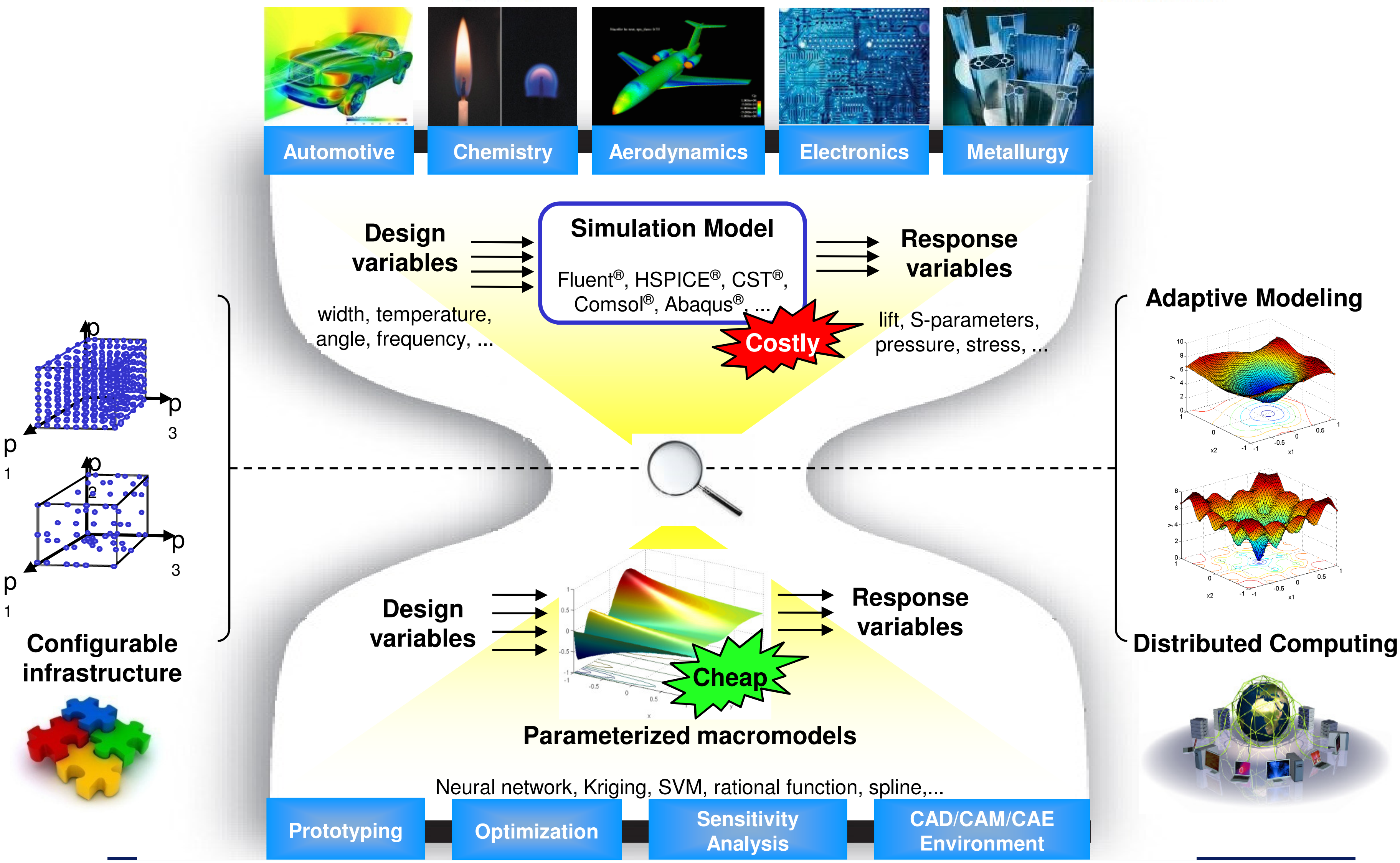

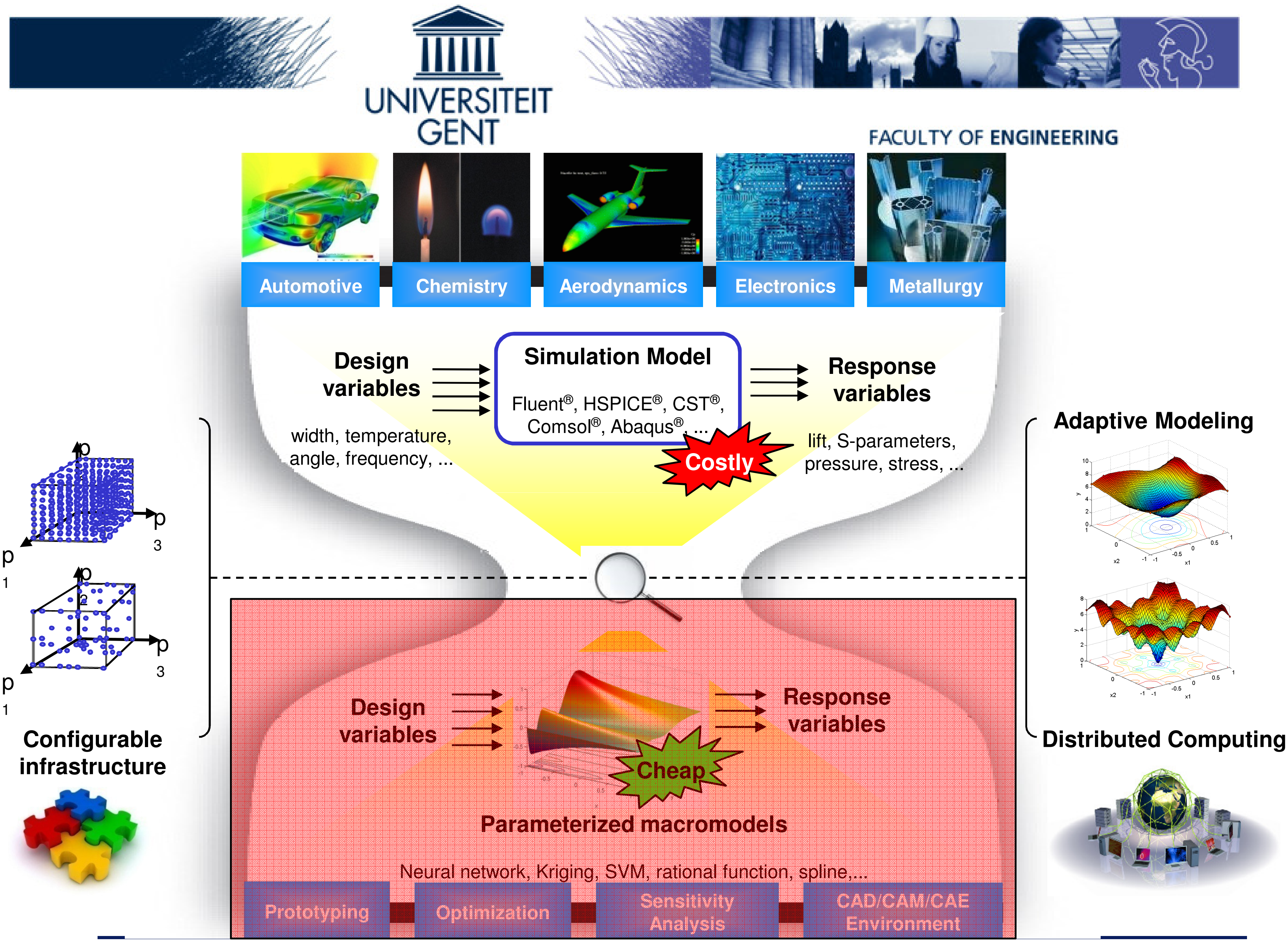
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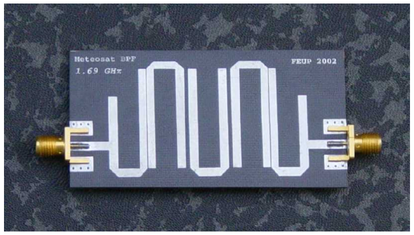
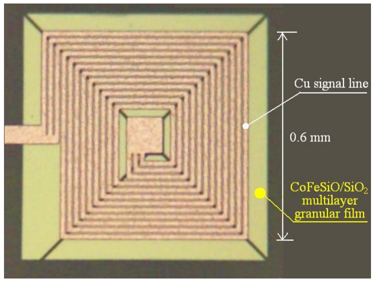
Automotive
Chemistry
Aerodynamics
Electronics
Metallurgy
Design variables
Simulation Model
Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...
Response variables
width, temperature, angle, frequency, ...
Costly
lift, S-parameters, pressure, stress, ...
Adaptive Modeling
Configurable infrastructure
Design variables
Response variables
Cheap
Parameterized macromodels
Neural network, Kriging, SVM, rational function, spline,...
Prototyping
Optimization
Sensitivity Analysis
CAD/CAM/CAE Environment
Distributed Computing


SONY
Cyber-shot
7.2


DELL


FEUP 2002


Cu signal line
0.6 mm
$CoFeSiO/SiO_2$
multilayer
granular film

Design process

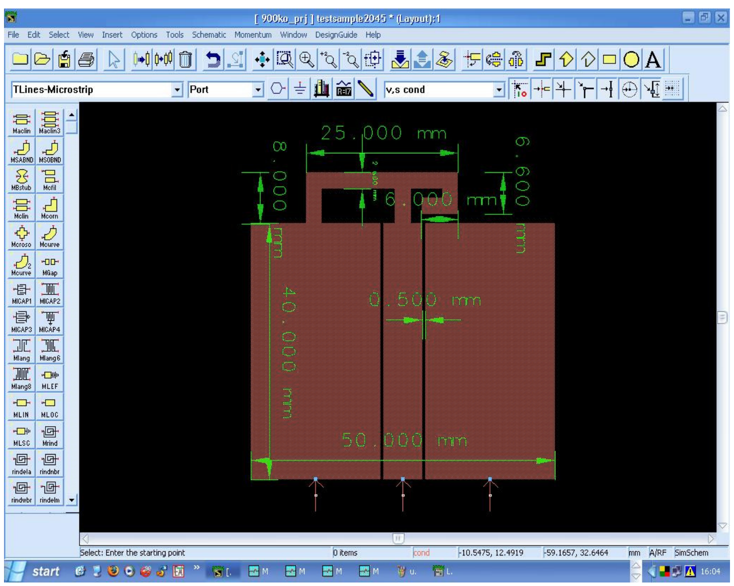
- several decisions
  - materials
  - geometrical dimensions
  - shape
  - constraints
    - space
    - cost
    - performance

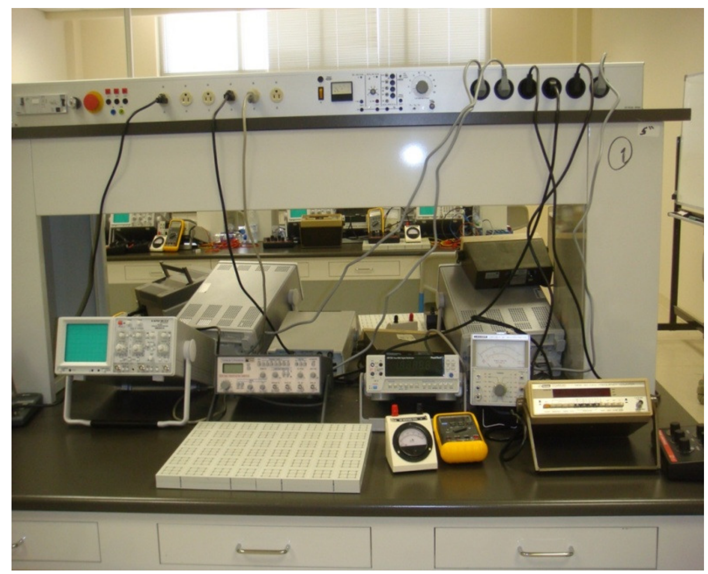
Simulators

- implementation of models
- describe systems behavior
- help designers

Measurements

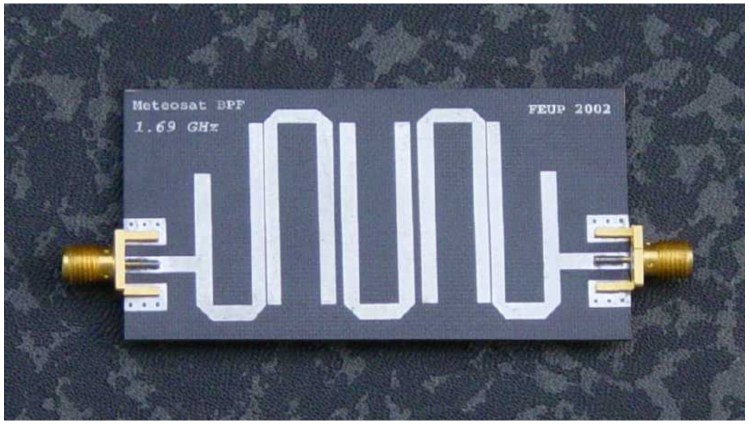
- post tuning
- verification
- help designers





A typical design process requires

- design space optimization
- design space exploration
- sensitivity analysis
  - multiple simulations (measurements)
  - different design parameters values (e.g. layout features)



A typical design process requires

- Multiple simulations (measurements)
  - computationally expensive (time and memory)

- Can we do better?

- Yes
  - By parameterized macromodels

Outline

Introduction

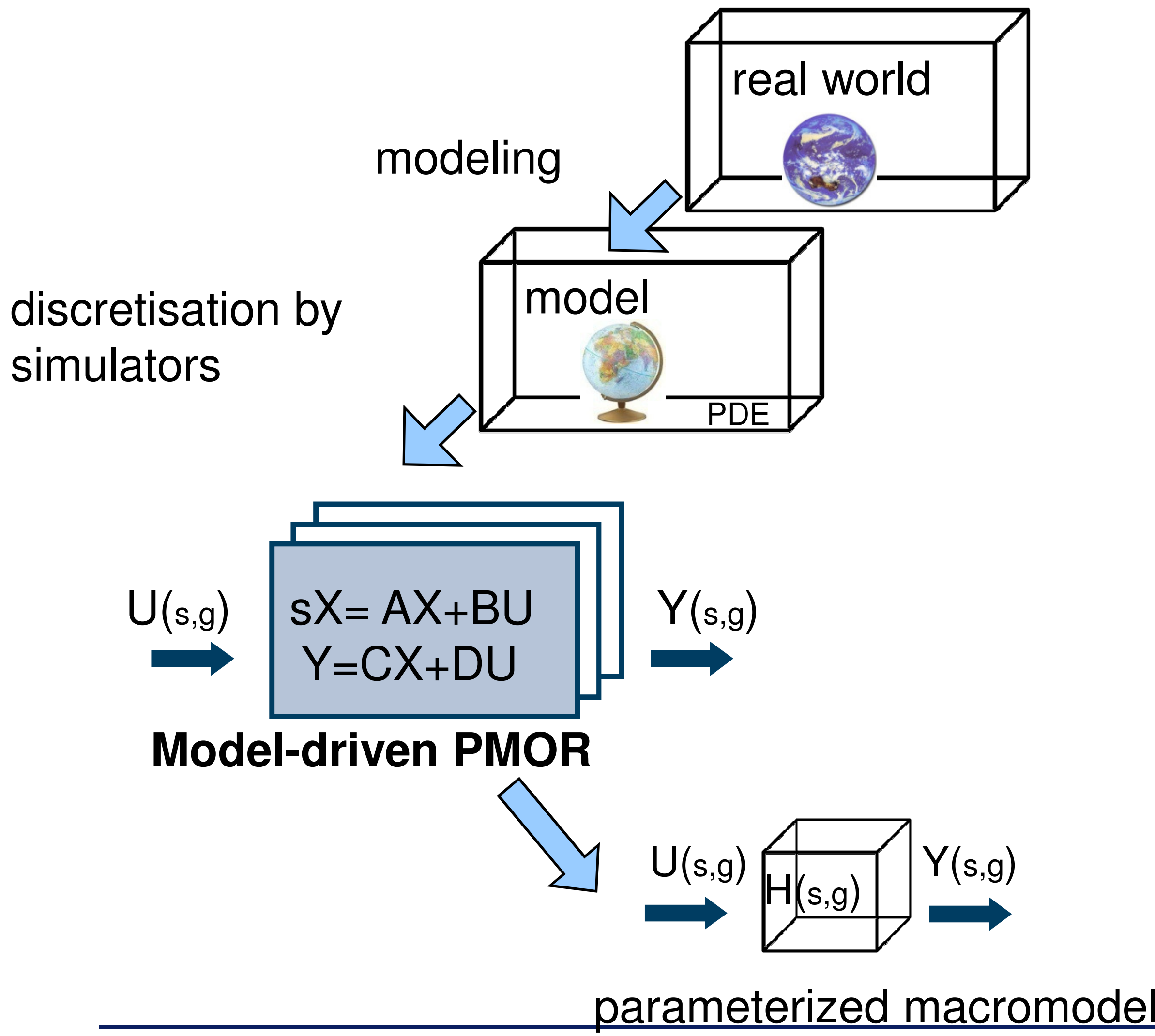
Parameterized Macromodels

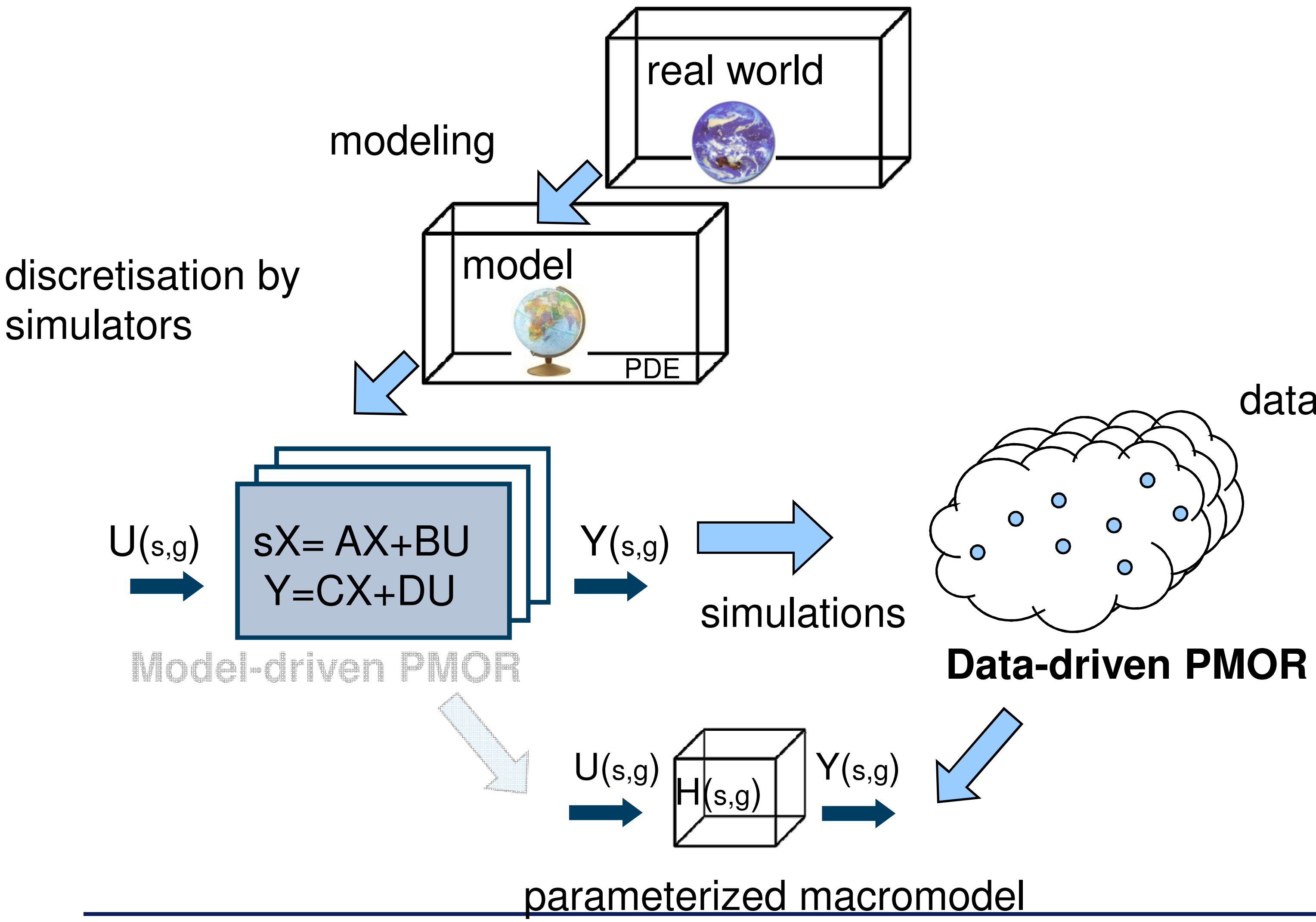
New interpolation with scaling-shifting coefficients

Numerical examples

- Spiral inductor
- PCB

Conclusions


real world
modeling
model
PDE
discretisation by simulators
U(s,g)
sX= AX+BU
Y=CX+DU
Y(s,g)
Model-driven PMOR
U(s,g)
H(s,g)
Y(s,g)
parameterized macromodel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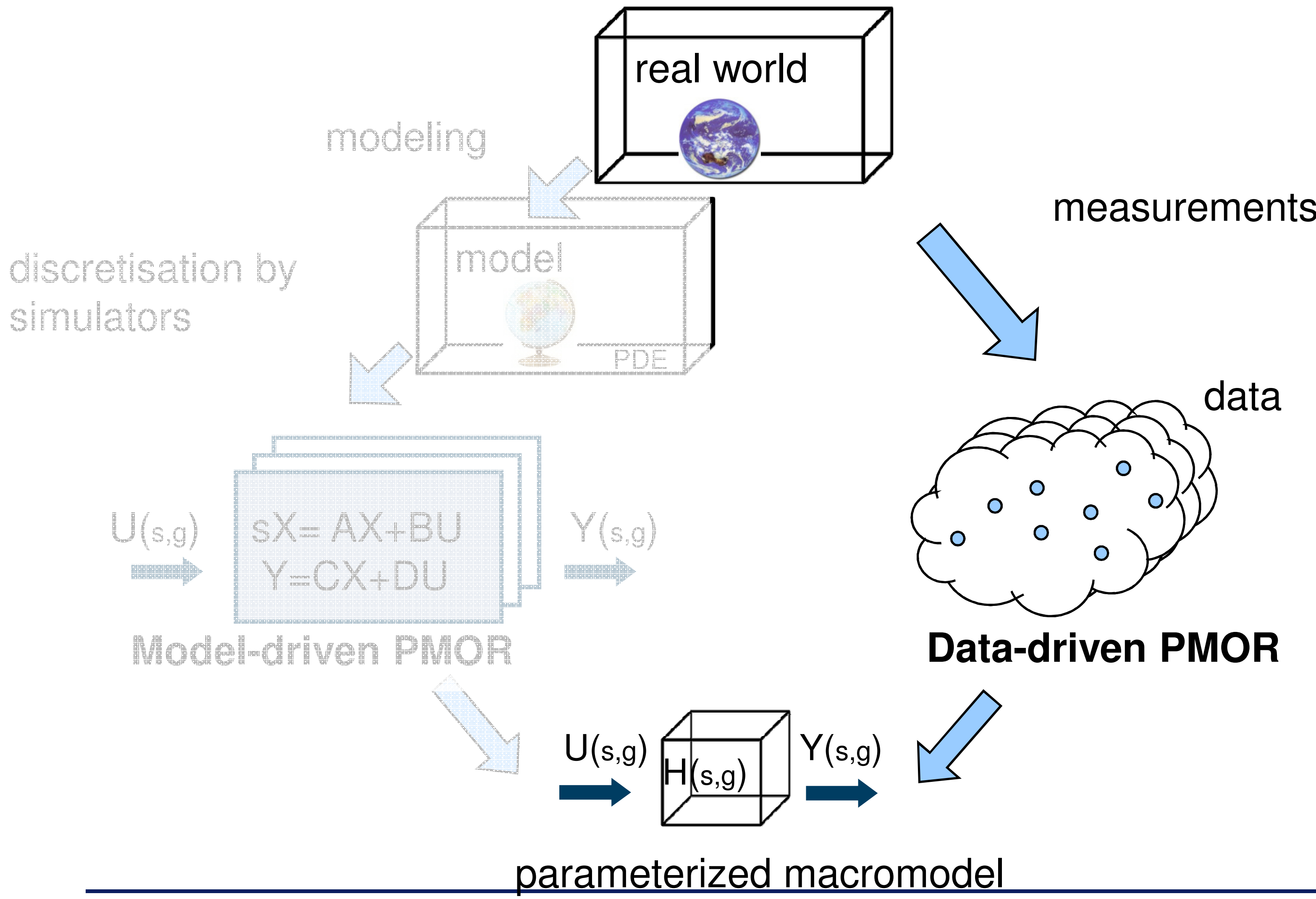
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Model-driven PMOR
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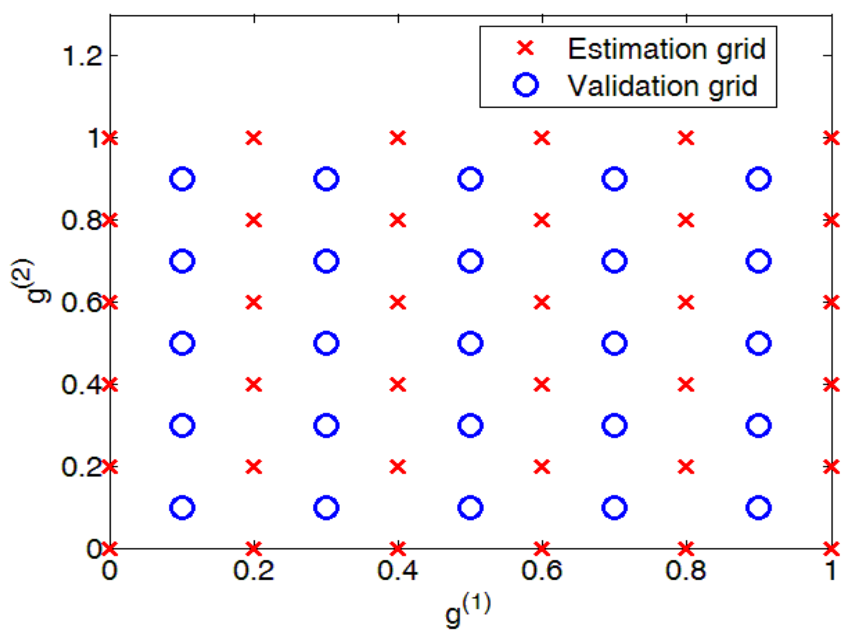
H(s,g)
Y(s,g)
parameterized macromodel

PMOR concepts

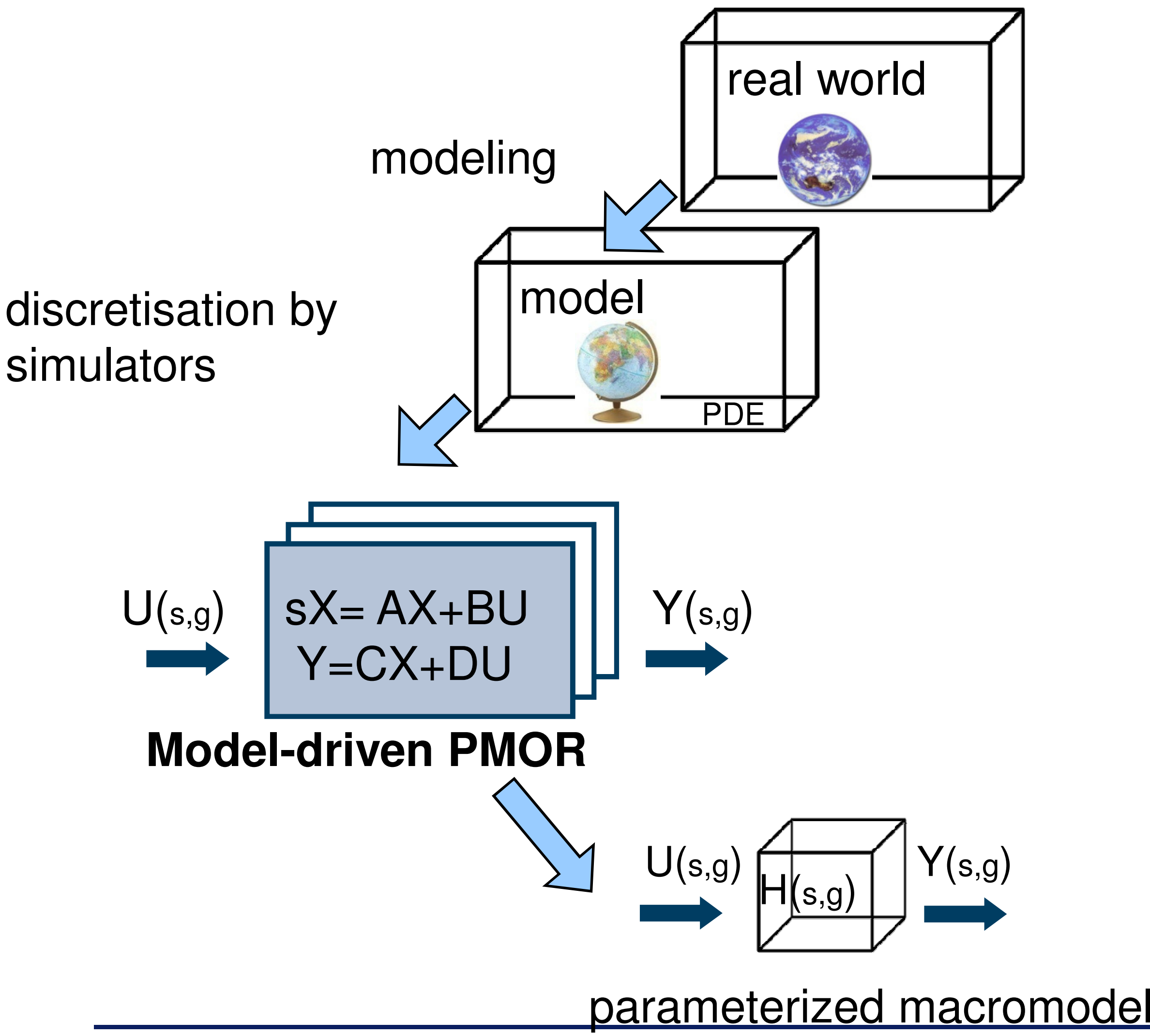
Two design space grids are used in the modeling process

- **estimation grid**
- **validation grid**

Design space



$$g = \left(g^{(n)}\right)_{n=1}^{N}$$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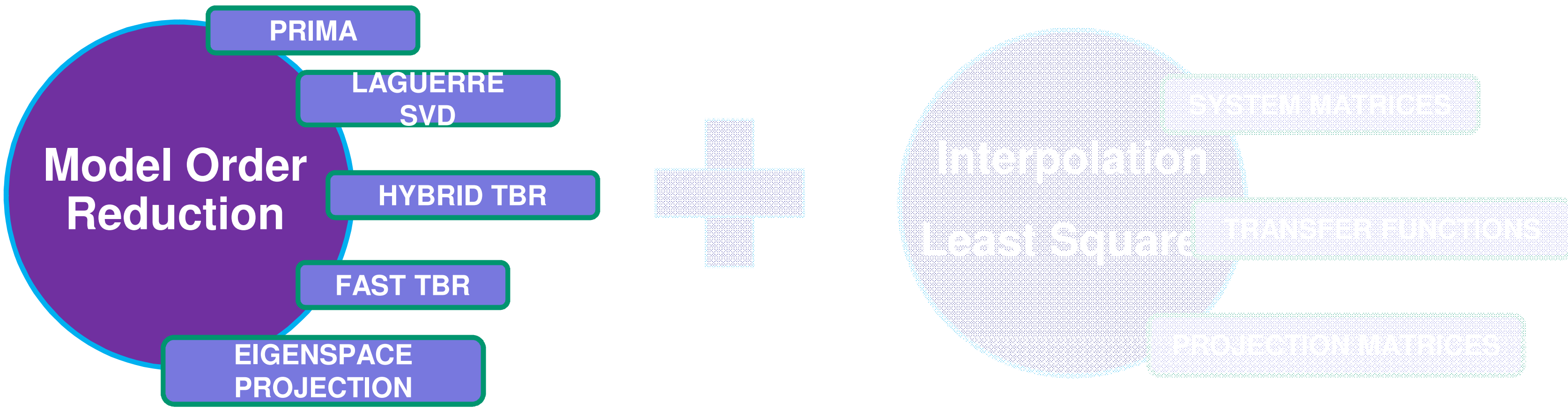
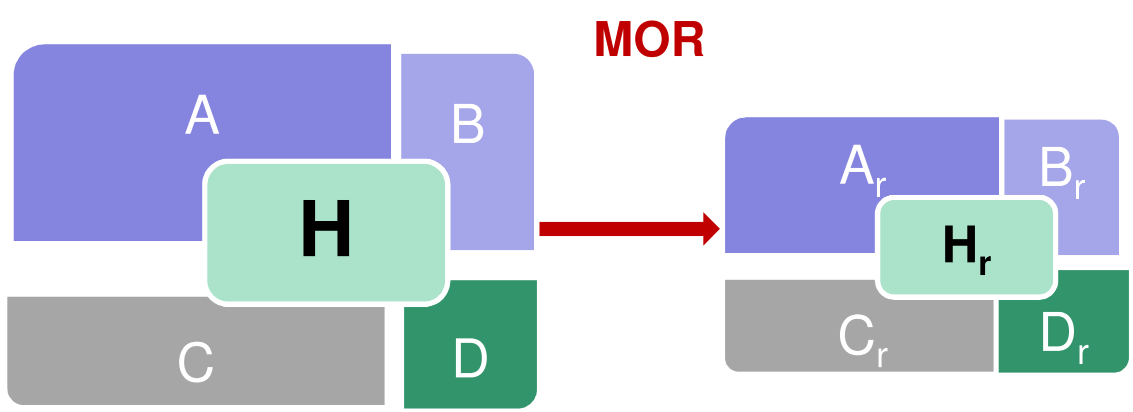
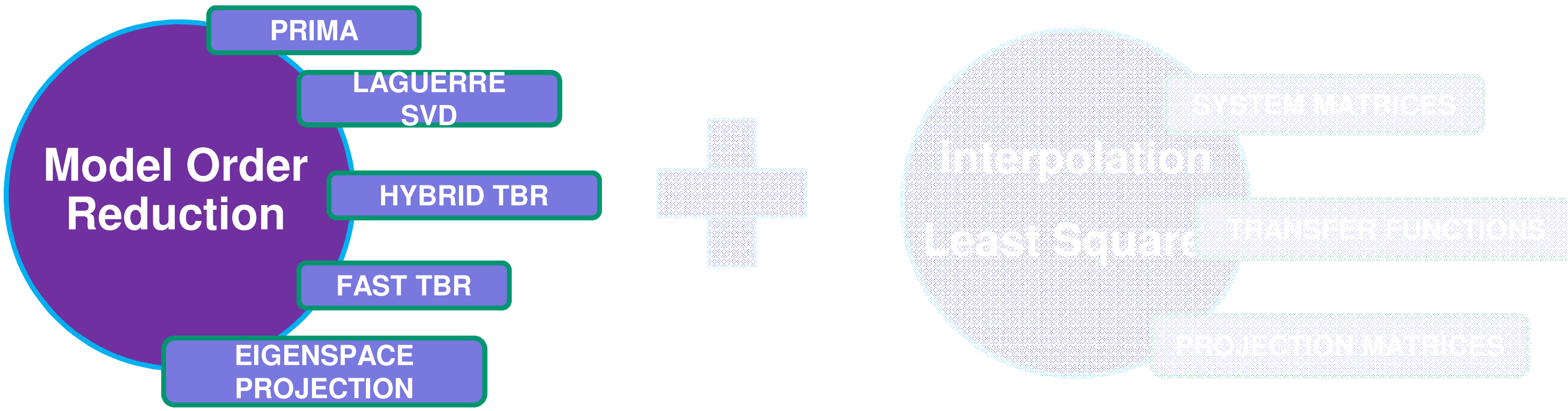

Model Order Reduction
PRIMA
LAGUERRE SVD
HYBRID TBR
FAST TBR
EIGENSPACE PROJECTION
Interpolation
Least Square
SYSTEM MATRICES
TRANSFER FUNCTIONS
PROJECTION MATRICES


MOR
A
B
H
C
D
A_r
B_r
H_r
C_r
D_r


Model Order Reduction
PRIMA
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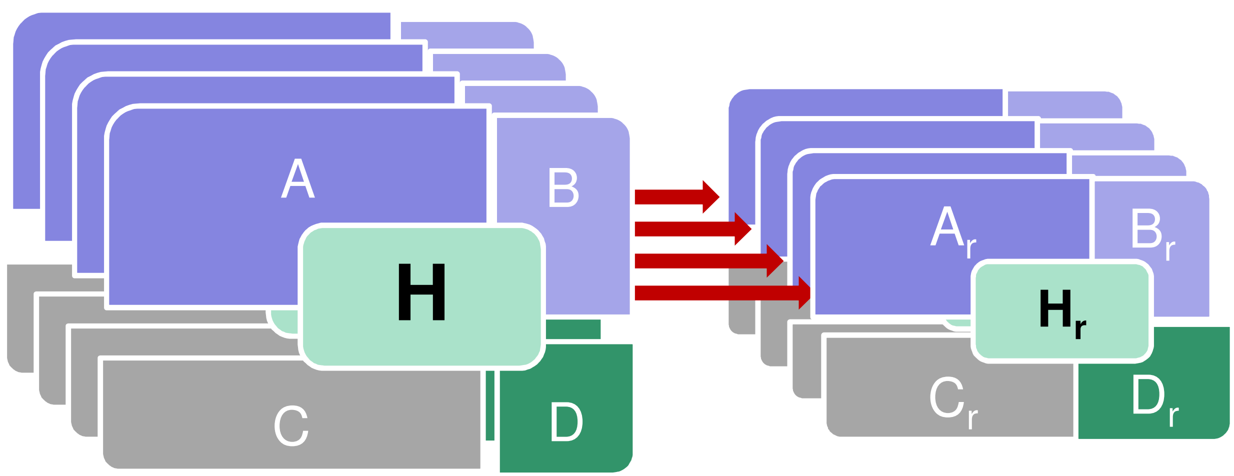
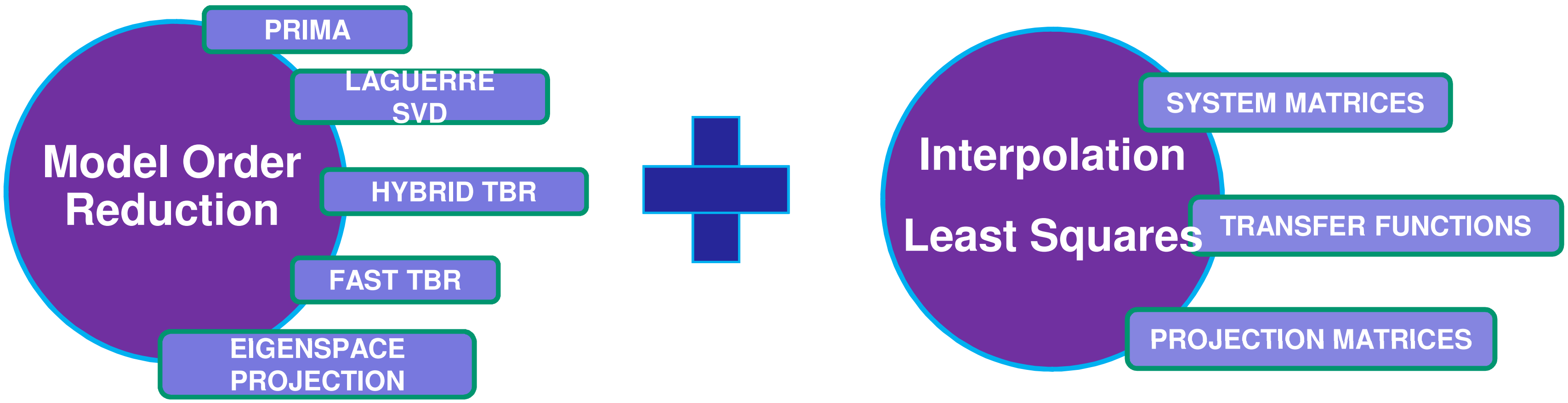
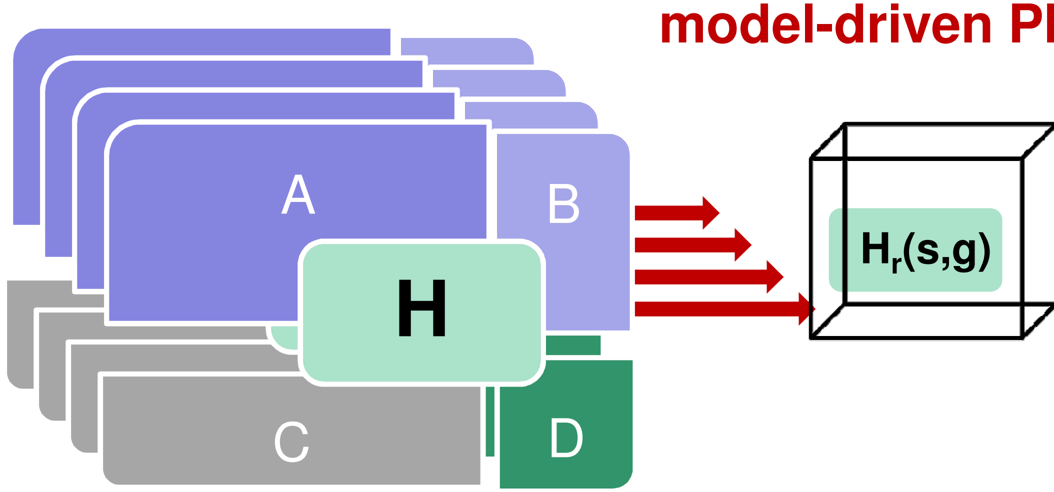
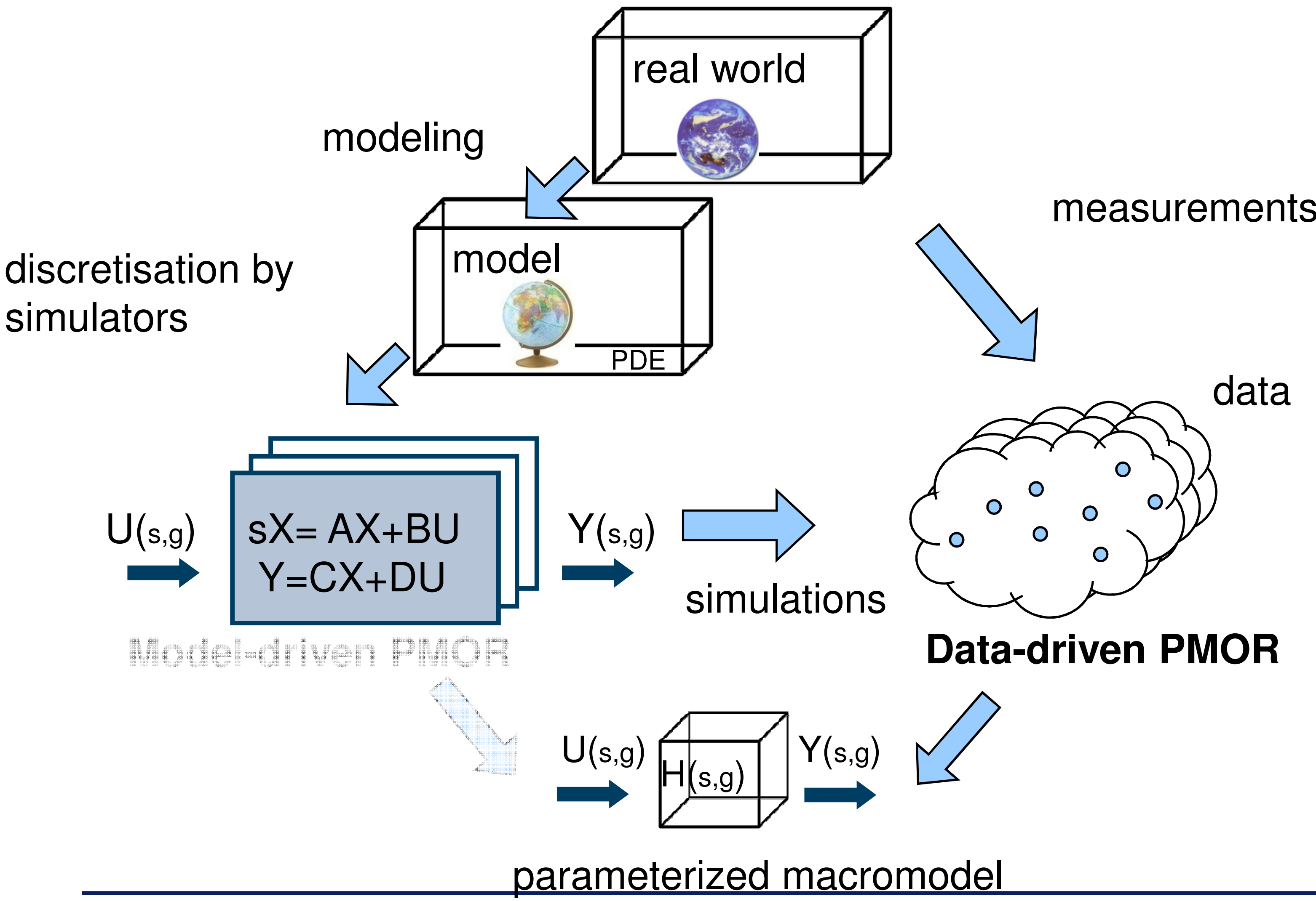

A
B
H
C
D
A_r
B_r
H_r
C_r
D_r



model-driven PMOR



- accuracy
- efficiency
- stability guaranteed
- passivity guaranteed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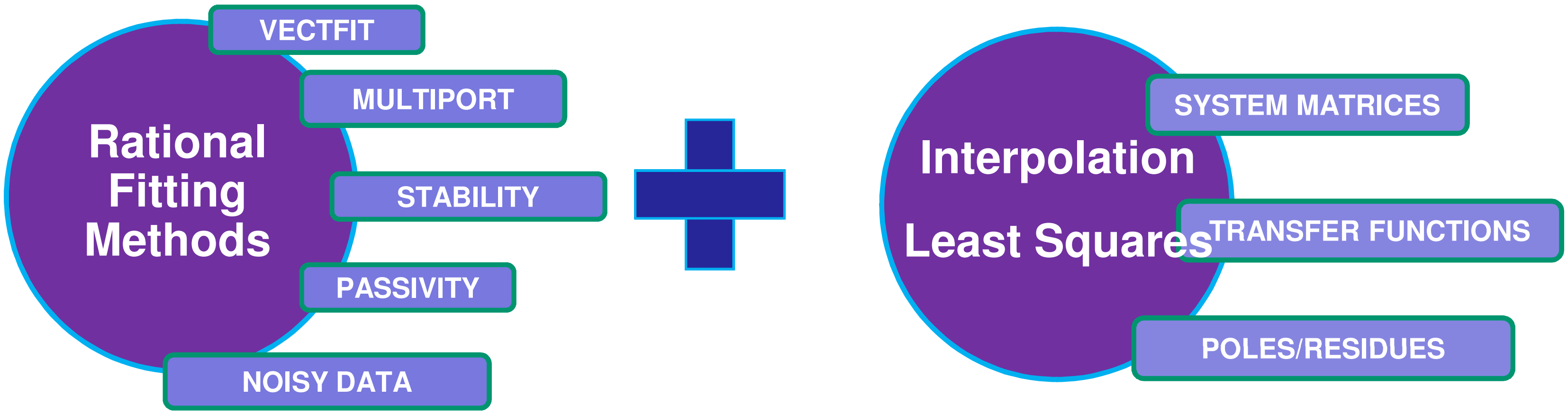
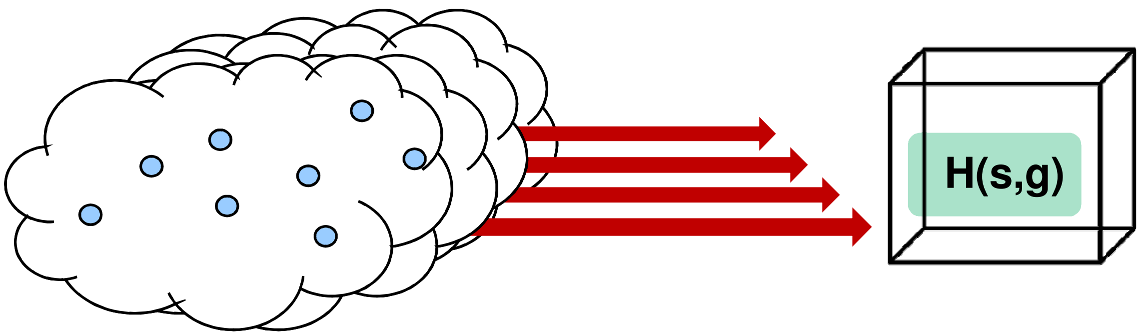
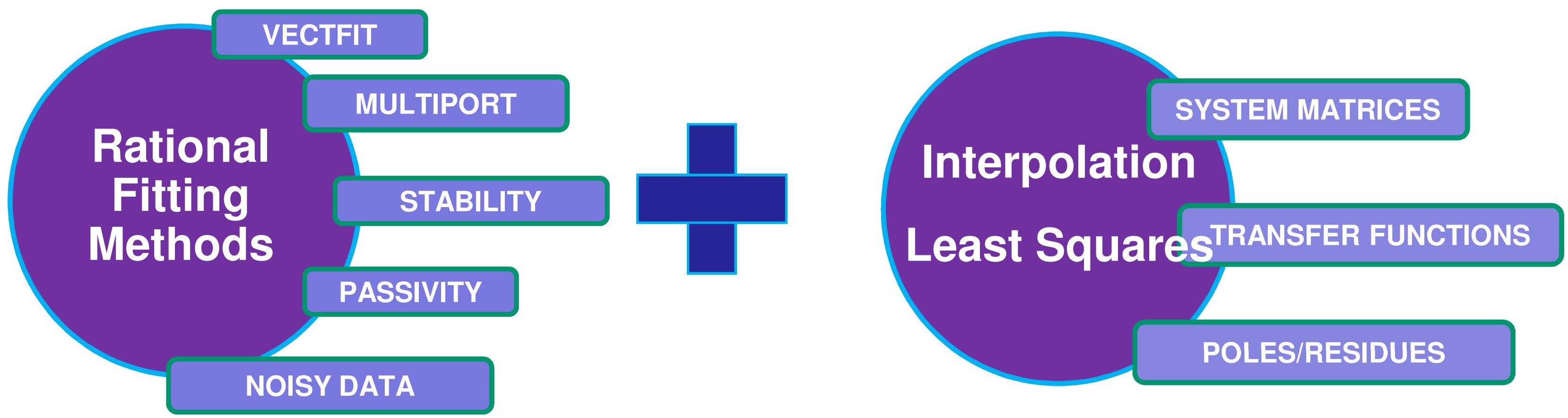


data-driven PMOR

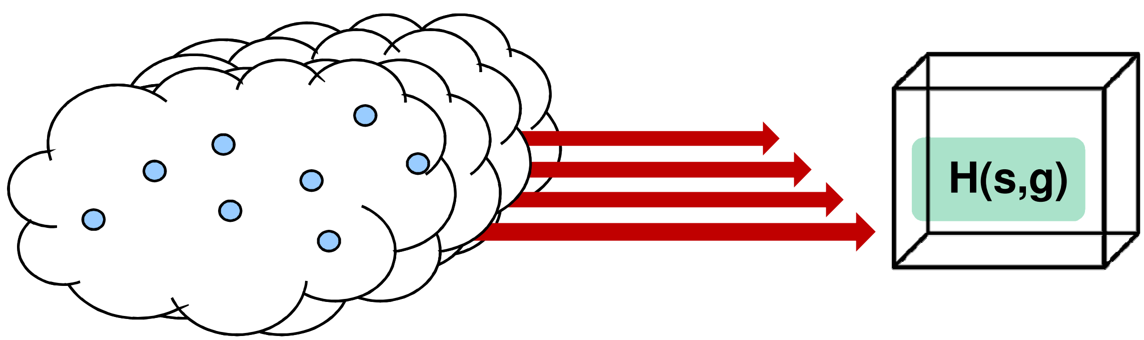


- accuracy
- efficiency
- stability guaranteed
- passivity guaranteed

scattered data



data-driven PMOR



$$\mathbf{H}(s,\mathbf{g}) = \sum_{p=1}^{P} \frac{\mathbf{Q}(\mathbf{g})}{s - a_p(\mathbf{g})}$$

$$\mathbf{H}(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$

scattered data

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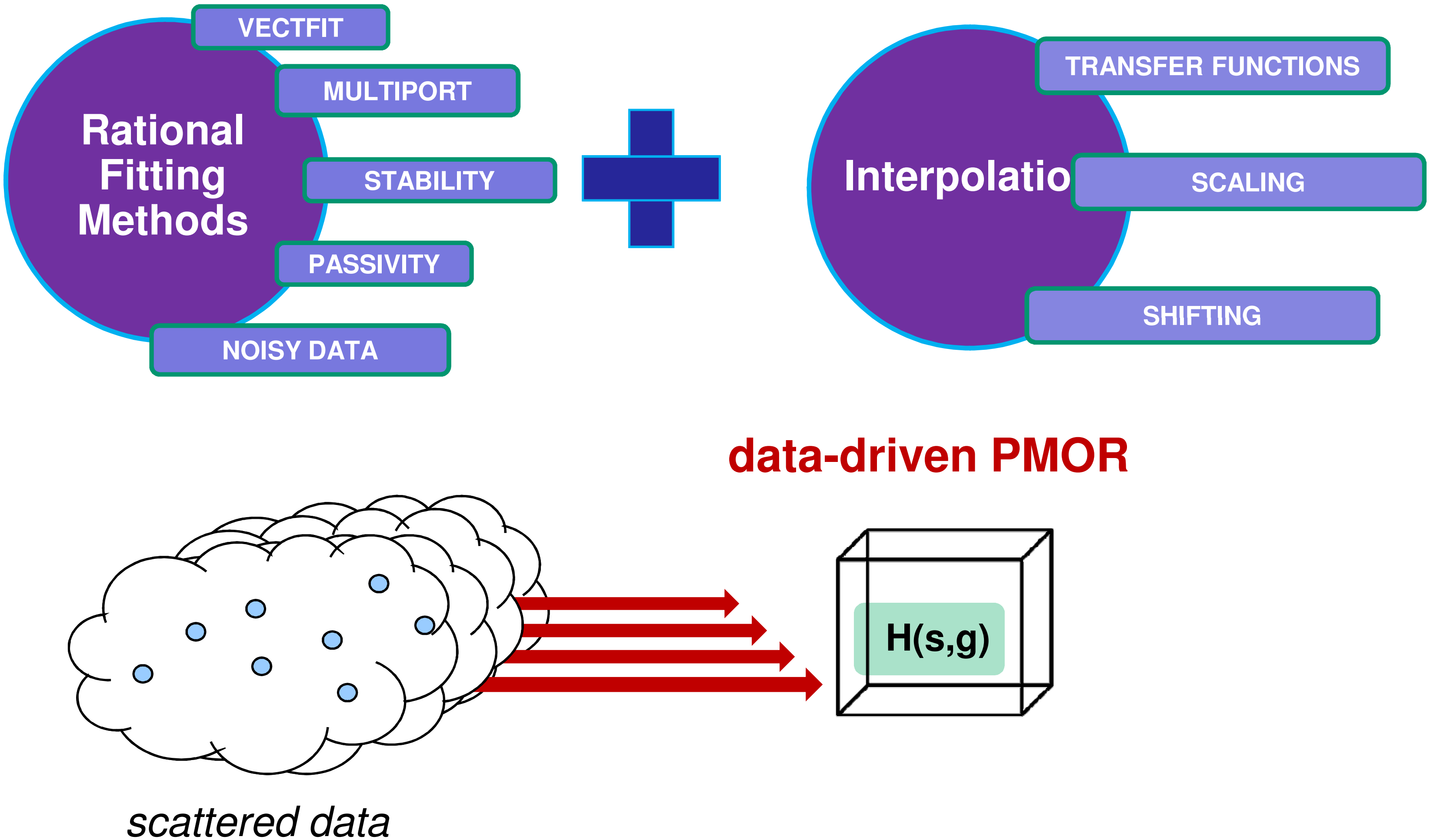
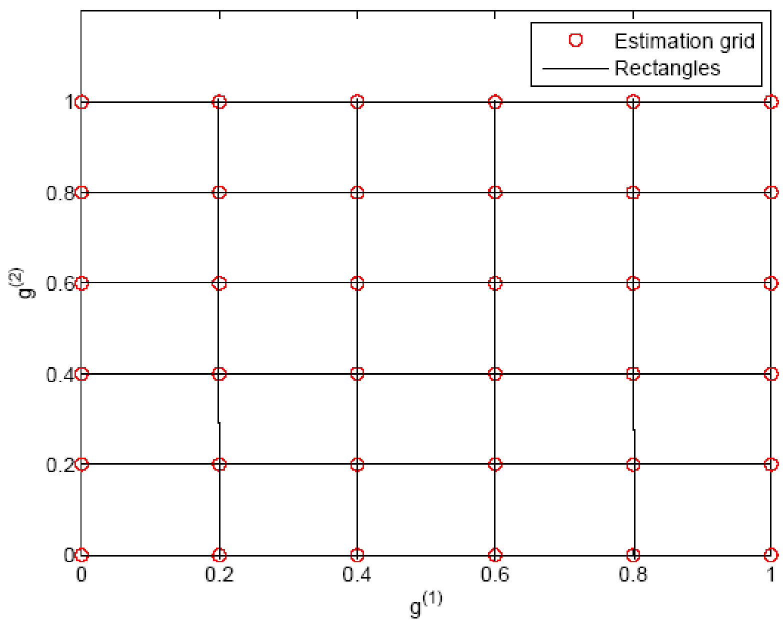
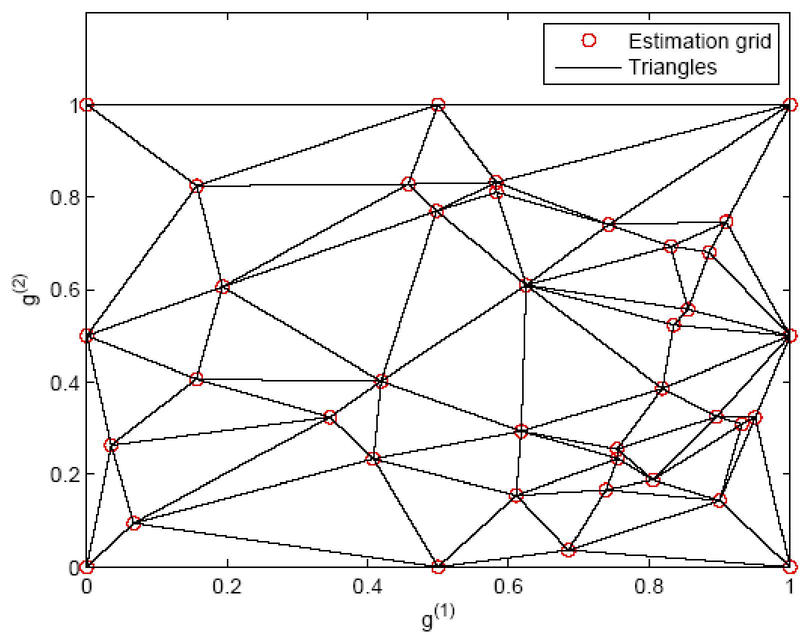

Rational Fitting Methods
VECTFIT
MULTIPORT
STABILITY
PASSIVITY
NOISY DATA
Interpolatio
TRANSFER FUNCTIONS
SCALING
SHIFTING
data-driven PMOR
H(s,g)
scattered data

Features

- **local approach (cell by cell)**

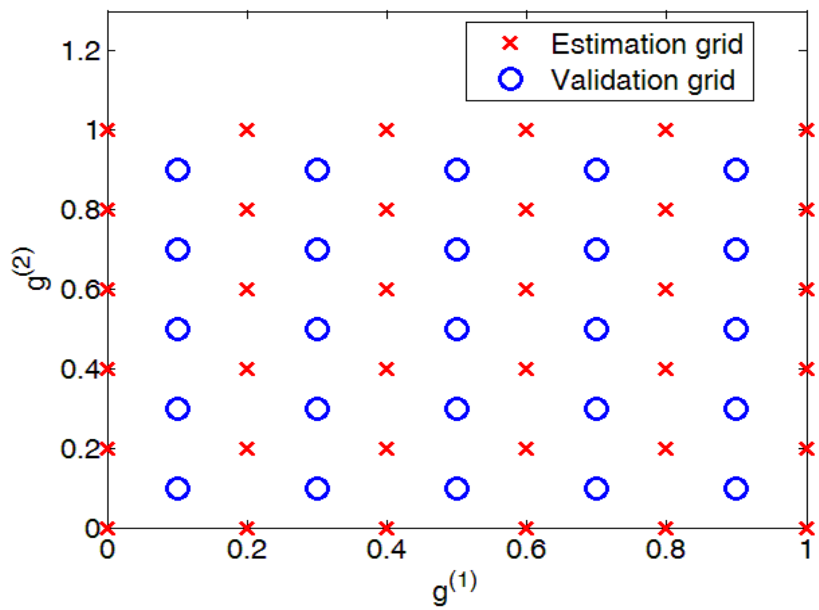




Features

- local approach (cell by cell)
- independent from a specific state-space realization
- stability and passivity guaranteed over the design space
- suitable to robust adaptive sampling
- different flavours

Design space $g = (g^{(n)})_{n=1}^{N}$



Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid

↓

Compute scaling and frequency shifting coefficients
$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$
in the estimation design space grid

↓

Multivariate interpolation of
scaling and frequency shifting coefficients
$\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

↓

Multivariate interpolation of
scaled and shifted root macromodels
$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$

Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid

$\downarrow$

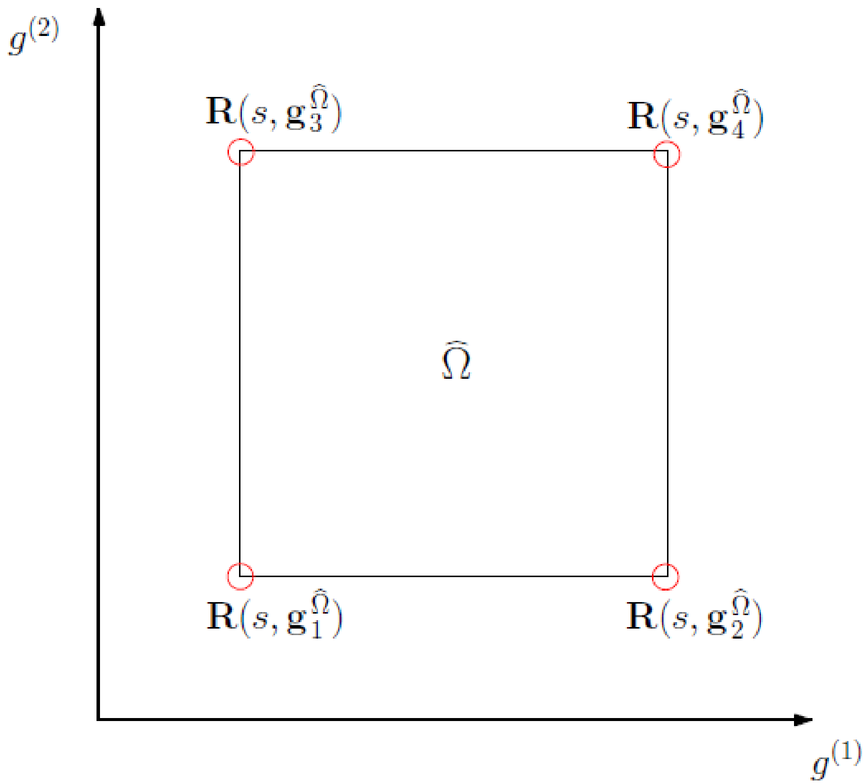
Compute scaling and frequency shifting coefficients
$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$
in the estimation design space grid

$\downarrow$

Multivariate interpolation of
scaling and frequency shifting coefficients
$\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

$\downarrow$

Multivariate interpolation of
scaled and shifted root macromodels
$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$



$$\mathbf{R}(s, \mathbf{g}_j^{\widehat{\Omega}}) = \mathbf{C}_0(\mathbf{g}_j^{\widehat{\Omega}}) + \sum_{n=1}^{N(\widehat{\Omega})} \frac{\mathbf{C}_n(\mathbf{g}_j^{\widehat{\Omega}})}{s - \mathbf{p}_n(\mathbf{g}_j^{\widehat{\Omega}})}$$

Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid

$\downarrow$

$\boxed{\text{Compute scaling and frequency shifting coefficients } \alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i}) \text{ in the estimation design space grid}}$

$\downarrow$

Multivariate interpolation of
scaling and frequency shifting coefficients
$\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

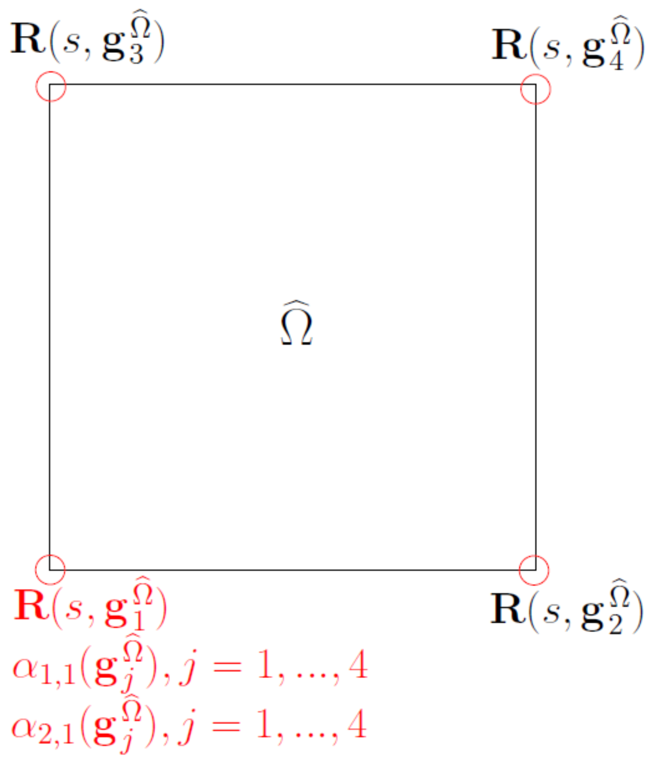
$\downarrow$

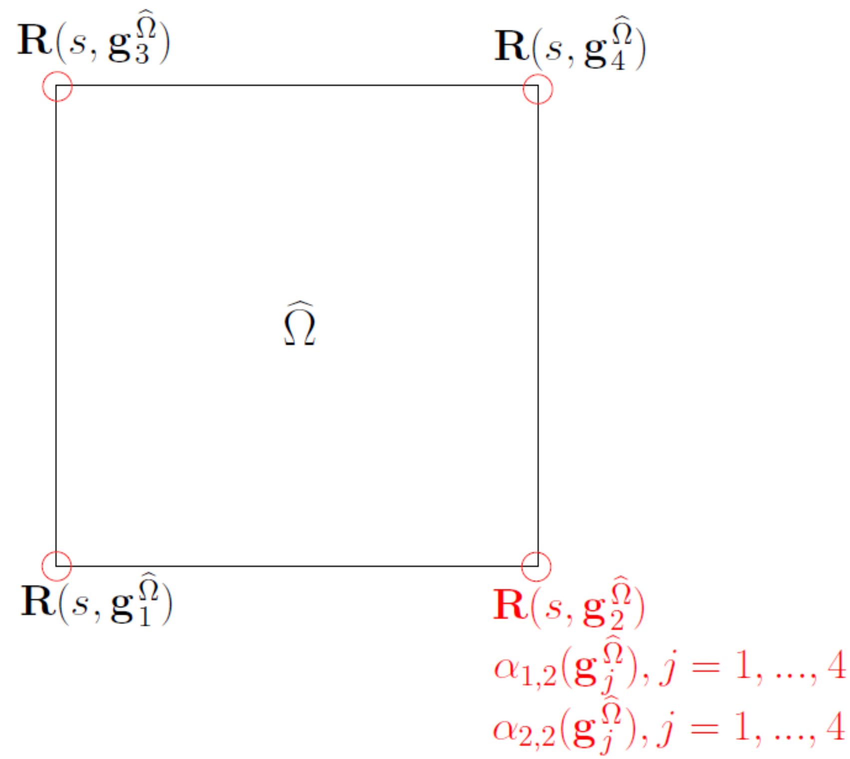
Multivariate interpolation of
scaled and shifted root macromodels
$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$

$$\min_{\alpha_{1,k}(\mathbf{g}_j^{\widehat{\Omega}}),\,\alpha_{2,k}(\mathbf{g}_j^{\widehat{\Omega}})} Err(\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}),\mathbf{R}(s,\boldsymbol{g}_j^{\widehat{\Omega}}))$$

$$\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}) = \alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}})\mathbf{R}(s\alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}),\boldsymbol{g}_k^{\widehat{\Omega}})$$

$$\alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = \alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = 1,\ \ j = k$$

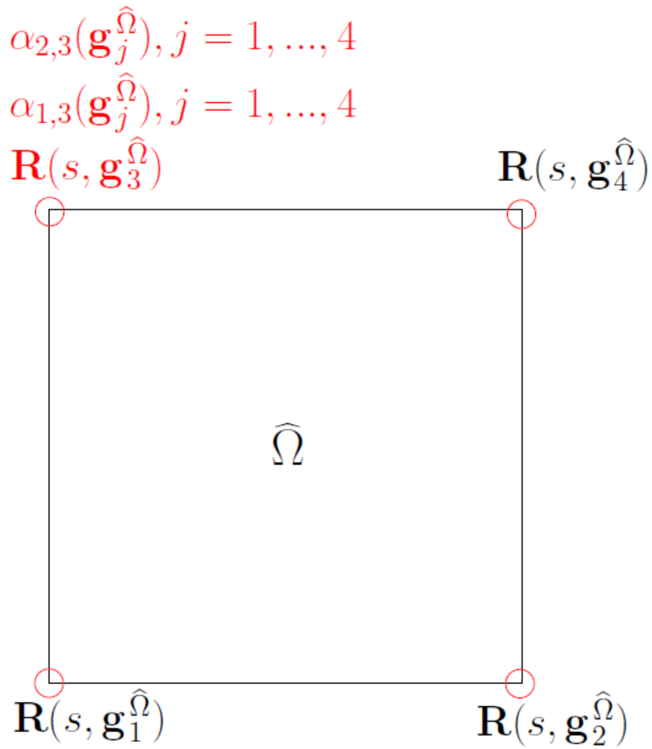


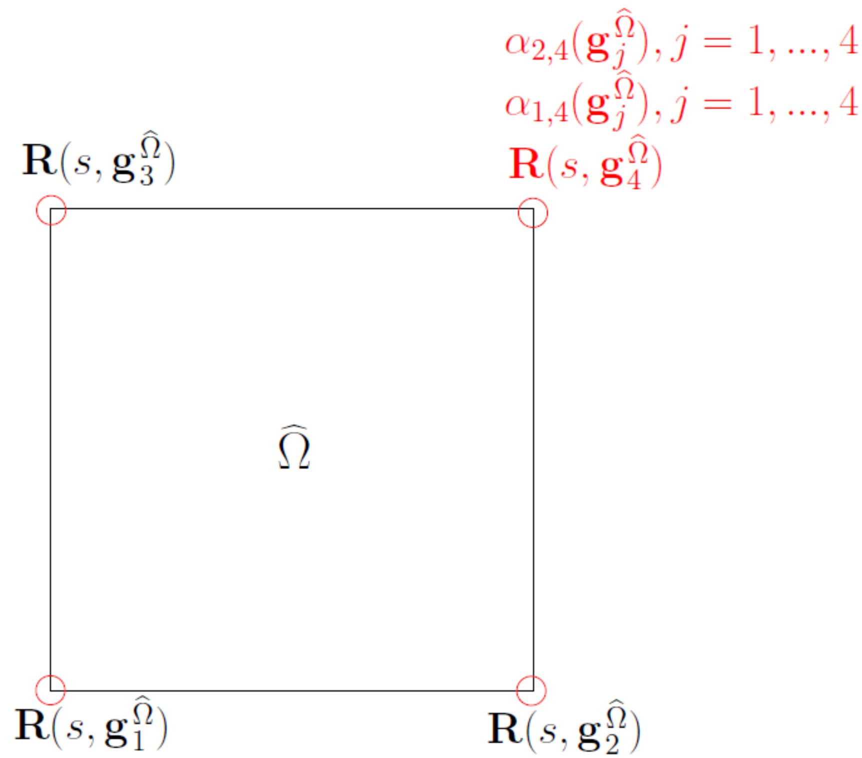


$$\min_{\alpha_{1,k}(\mathbf{g}_j^{\widehat{\Omega}}),\alpha_{2,k}(\mathbf{g}_j^{\widehat{\Omega}})} Err(\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}),\mathbf{R}(s,\boldsymbol{g}_j^{\widehat{\Omega}}))$$

$$\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}) = \alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}})\mathbf{R}(s\alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}),\boldsymbol{g}_k^{\widehat{\Omega}})$$

$$\alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = \alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = 1,\ \ j = k$$





Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid

↓

Compute scaling and frequency shifting coefficients
$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$
in the estimation design space grid

↓

$\boxed{\text{Multivariate interpolation of scaling and frequency shifting coefficients } \alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})}$

↓

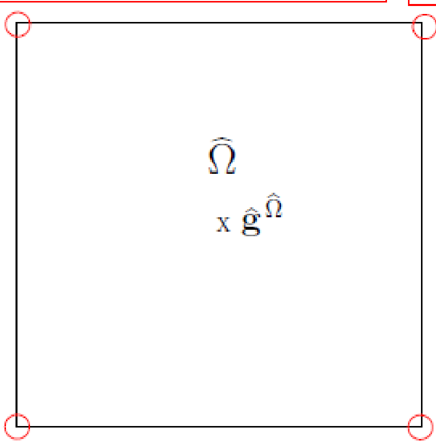
Multivariate interpolation of
scaled and shifted root macromodels
$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$

$\alpha_{1,3}(\hat{\mathbf{g}}^{\widehat{\Omega}})\mathbf{R}(\alpha_{2,3}(\hat{\mathbf{g}}^{\widehat{\Omega}})s, \mathbf{g}_3^{\widehat{\Omega}})$

$\alpha_{1,4}(\hat{\mathbf{g}}^{\widehat{\Omega}})\mathbf{R}(\alpha_{2,4}(\hat{\mathbf{g}}^{\widehat{\Omega}})s, \mathbf{g}_4^{\widehat{\Omega}})$

$\alpha_{2,3}(\hat{\mathbf{g}}^{\widehat{\Omega}}) = interp(\mathbf{g}_j^{\widehat{\Omega}}, \alpha_{2,3}(\mathbf{g}_j^{\widehat{\Omega}}), \hat{\mathbf{g}}^{\widehat{\Omega}})$
$\alpha_{1,3}(\hat{\mathbf{g}}^{\widehat{\Omega}}) = interp(\mathbf{g}_j^{\widehat{\Omega}}, \alpha_{1,3}(\mathbf{g}_j^{\widehat{\Omega}}), \hat{\mathbf{g}}^{\widehat{\Omega}})$
$\mathbf{R}(s, \mathbf{g}_3^{\widehat{\Omega}})$

$\alpha_{2,4}(\hat{\mathbf{g}}^{\widehat{\Omega}}) = interp(\mathbf{g}_j^{\widehat{\Omega}}, \alpha_{2,4}(\mathbf{g}_j^{\widehat{\Omega}}), \hat{\mathbf{g}}^{\widehat{\Omega}})$
$\alpha_{1,4}(\hat{\mathbf{g}}^{\widehat{\Omega}}) = interp(\mathbf{g}_j^{\widehat{\Omega}}, \alpha_{1,4}(\mathbf{g}_j^{\widehat{\Omega}}), \hat{\mathbf{g}}^{\widehat{\Omega}})$
$\mathbf{R}(s, \mathbf{g}_4^{\widehat{\Omega}})$



$$\alpha_{1,k}(\hat{\boldsymbol{g}}^{\widehat{\Omega}}) = \sum_{k_1=1}^{2}\sum_{k_2=1}^{2} \alpha_{1,k}((g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\widehat{\Omega}})\ell_{k_1}(g^{(1)})\ell_{k_2}(g^{(2)})$$

$$\alpha_{2,k}(\hat{\boldsymbol{g}}^{\widehat{\Omega}}) = \sum_{k_1=1}^{2}\sum_{k_2=1}^{2} \alpha_{2,k}((g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\widehat{\Omega}})\ell_{k_1}(g^{(1)})\ell_{k_2}(g^{(2)})$$

$\mathbf{R}(s, \mathbf{g}_1^{\widehat{\Omega}})$
$\alpha_{1,1}(\hat{\mathbf{g}}^{\widehat{\Omega}}) = interp(\mathbf{g}_j^{\widehat{\Omega}}, \alpha_{1,1}(\mathbf{g}_j^{\widehat{\Omega}}), \hat{\mathbf{g}}^{\widehat{\Omega}})$
$\alpha_{2,1}(\hat{\mathbf{g}}^{\widehat{\Omega}}) = interp(\mathbf{g}_j^{\widehat{\Omega}}, \alpha_{2,1}(\mathbf{g}_j^{\widehat{\Omega}}), \hat{\mathbf{g}}^{\widehat{\Omega}})$

$\mathbf{R}(s, \mathbf{g}_2^{\widehat{\Omega}})$
$\alpha_{1,2}(\hat{\mathbf{g}}^{\widehat{\Omega}}) = interp(\mathbf{g}_j^{\widehat{\Omega}}, \alpha_{1,2}(\mathbf{g}_j^{\widehat{\Omega}}), \hat{\mathbf{g}}^{\widehat{\Omega}})$
$\alpha_{2,2}(\hat{\mathbf{g}}^{\widehat{\Omega}}) = interp(\mathbf{g}_j^{\widehat{\Omega}}, \alpha_{2,2}(\mathbf{g}_j^{\widehat{\Omega}}), \hat{\mathbf{g}}^{\widehat{\Omega}})$

$\alpha_{1,1}(\hat{\mathbf{g}}^{\widehat{\Omega}})\mathbf{R}(\alpha_{2,1}(\hat{\mathbf{g}}^{\widehat{\Omega}})s, \mathbf{g}_1^{\widehat{\Omega}})$

$\alpha_{1,2}(\hat{\mathbf{g}}^{\widehat{\Omega}})\mathbf{R}(\alpha_{2,2}(\hat{\mathbf{g}}^{\widehat{\Omega}})s, \mathbf{g}_2^{\widehat{\Omega}})$

Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid

↓

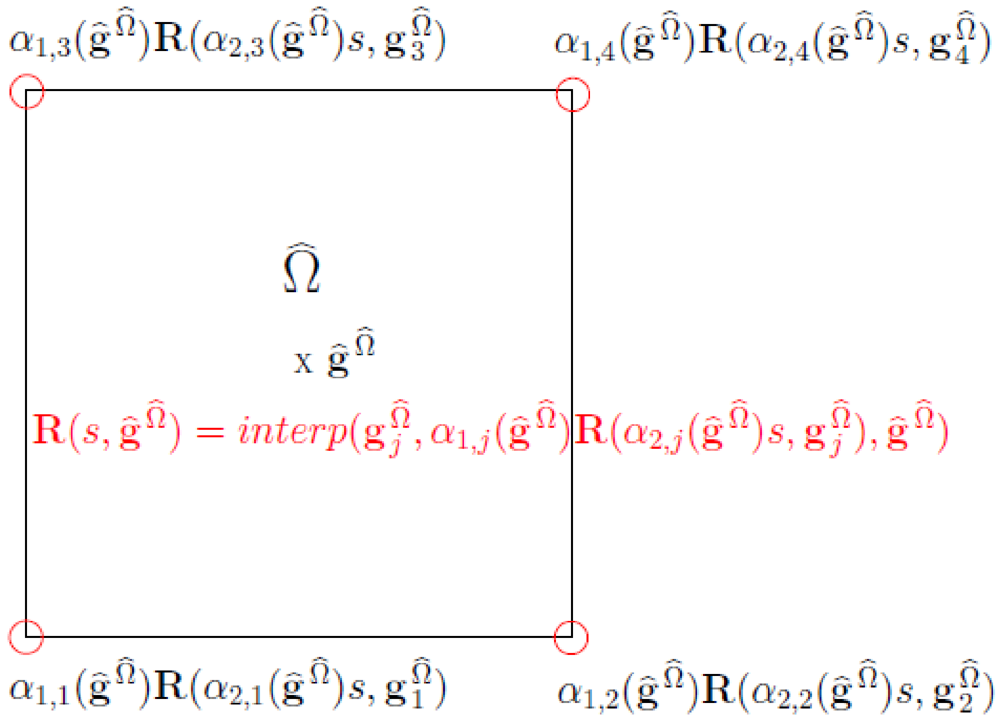
Compute scaling and frequency shifting coefficients
$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$
in the estimation design space grid

↓

Multivariate interpolation of
scaling and frequency shifting coefficients
$\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

↓

$\boxed{\text{Multivariate interpolation of scaled and shifted root macromodels } \alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})}$



$$\mathrm{R}(s, \widehat{g}^{\widehat{\Omega}}) = \sum_{k_1=1}^{2} \sum_{k_2=1}^{2} \widetilde{\mathrm{R}}(s, (g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\widehat{\Omega}}) \ell_{k_1}(g^{(1)}) \ell_{k_2}(g^{(2)})$$

Standard Interpolation

Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$ in the estimation design space grid

$\downarrow$

Multivariate interpolation of root macromodels $\mathbf{R}(s, \mathbf{g})$

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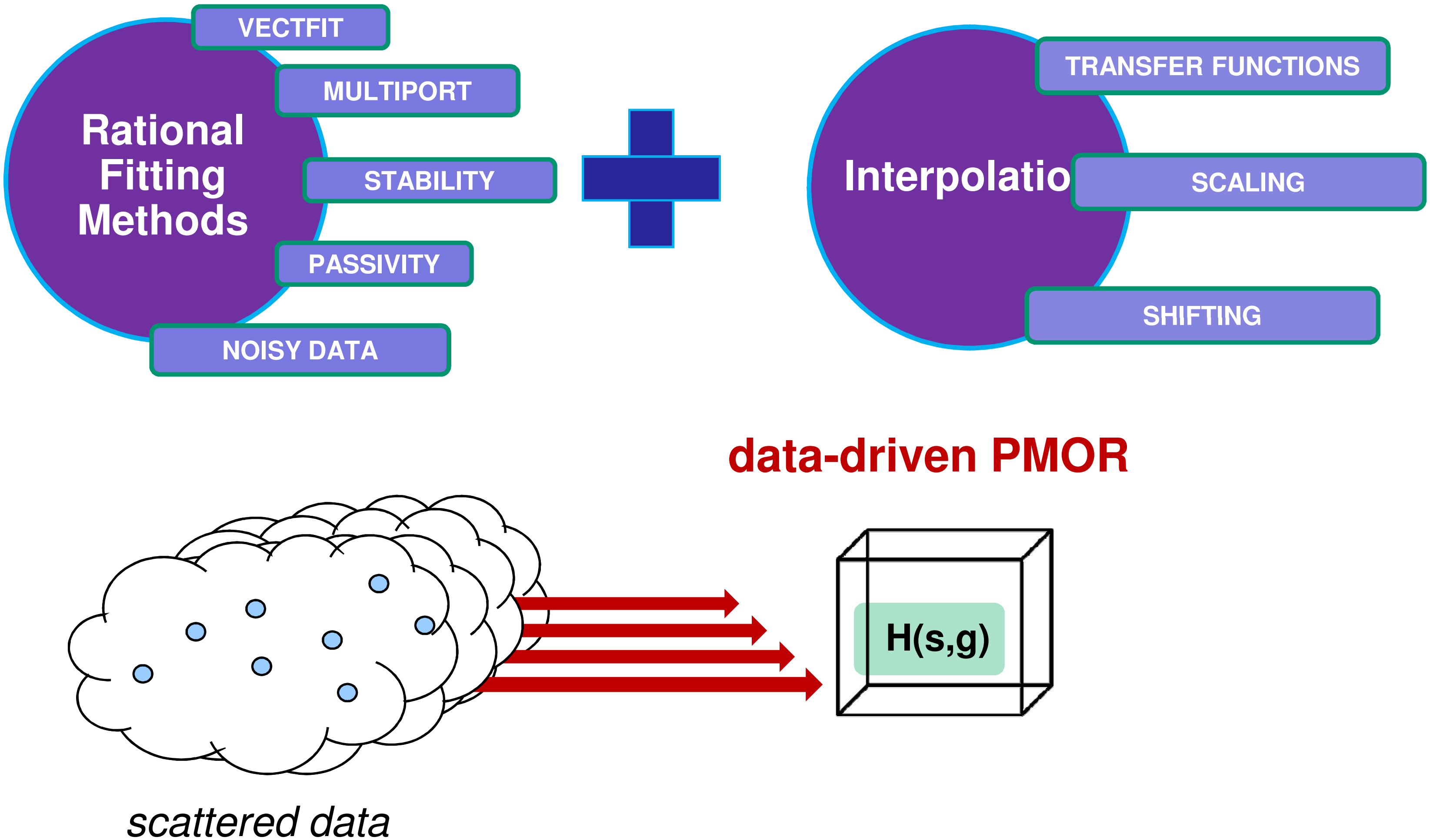
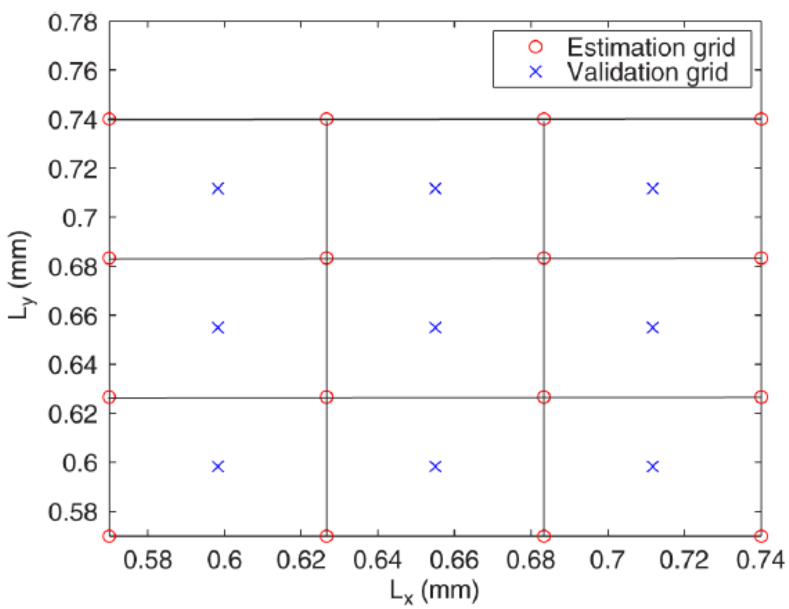
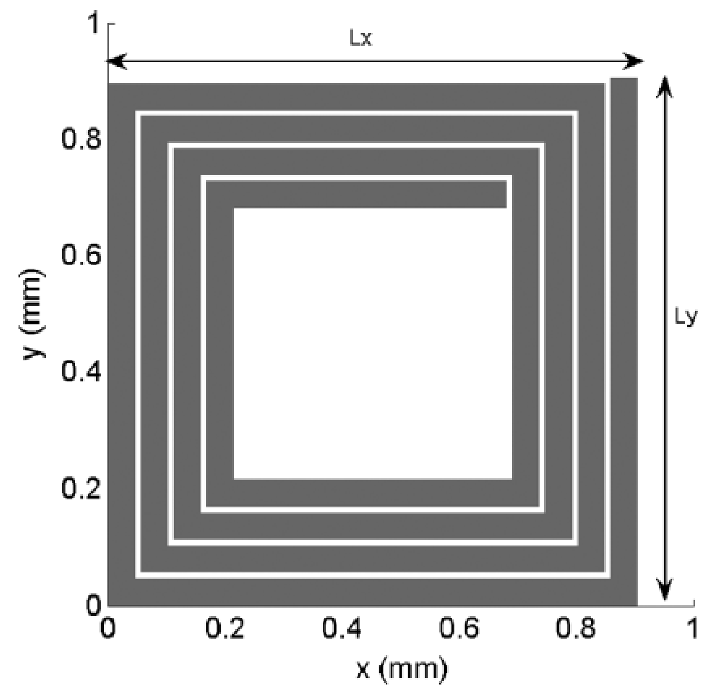

Rational Fitting Methods
VECTFIT
MULTIPORT
STABILITY
PASSIVITY
NOISY DATA
Interpolatio
TRANSFER FUNCTIONS
SCALING
SHIFTING
data-driven PMOR
H(s,g)
scattered data

3D example: Spiral inductor

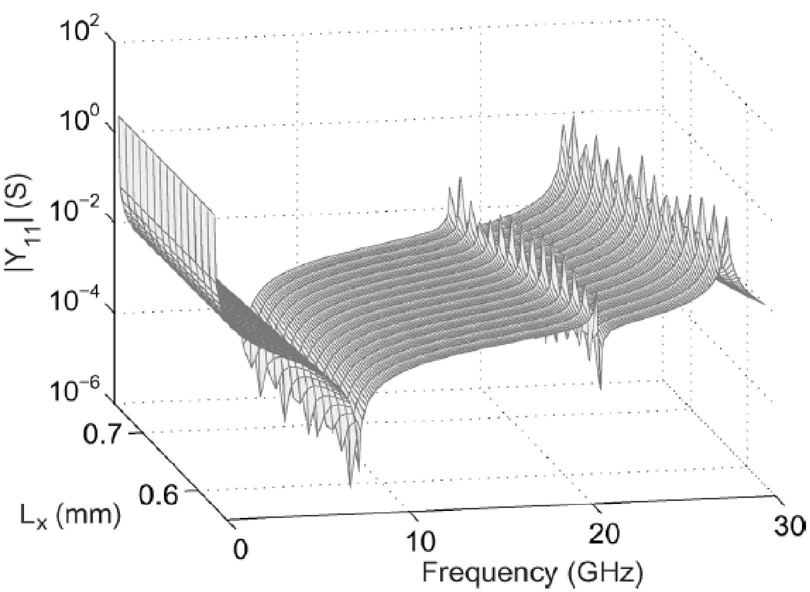
Parameter	Min	Max
Frequency ($freq$)	10 kHz	30 GHz
Horizontal length (L_x)	0.57 mm	0.74 mm
Vertical length (L_y)	0.57 mm	0.74 mm



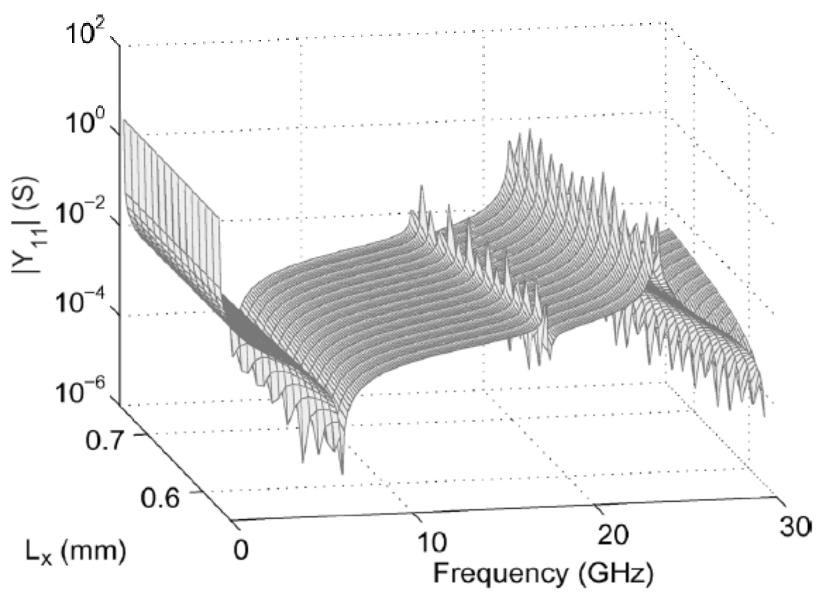


3D example: Spiral inductor

Ly = 0.57 mm

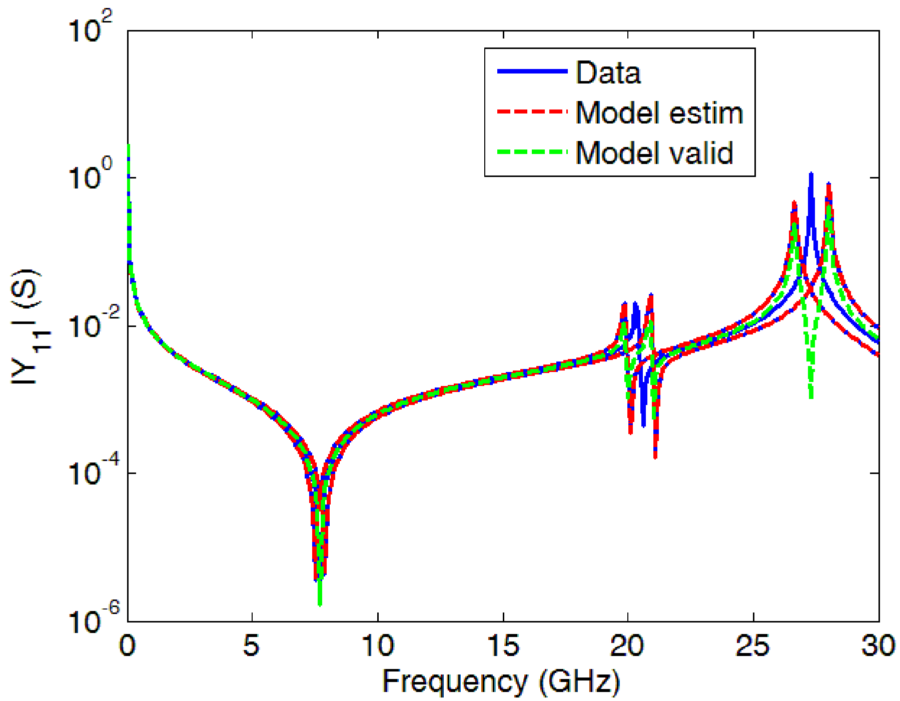


Ly = 0.74 mm



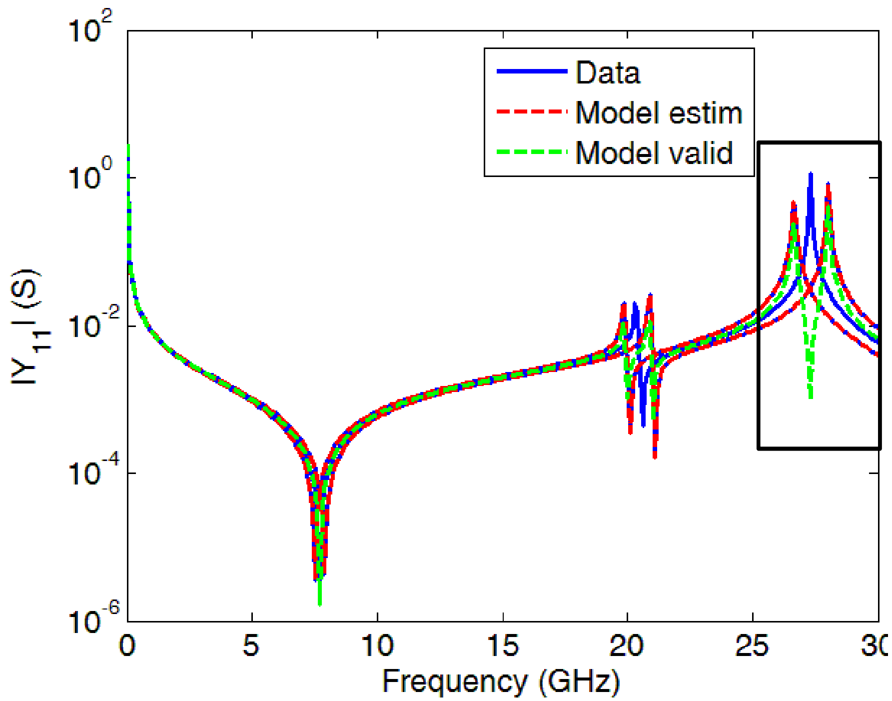
3D example: Spiral inductor (Without scaling-shifting coefficients)

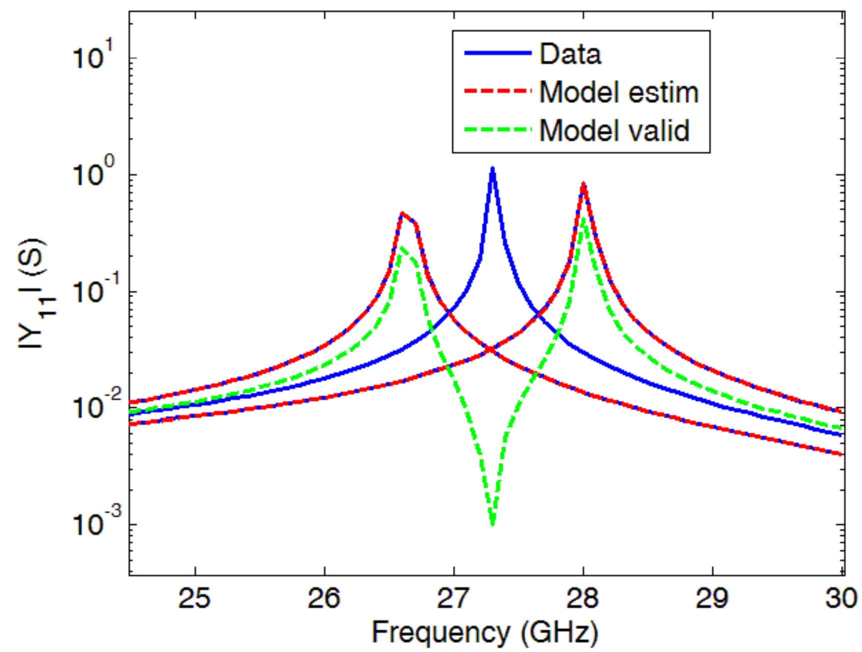
Lx = [0.57,0.60,0.63] mm, Ly = 0.57 mm



3D example: Spiral inductor (Without scaling-shifting coefficients)

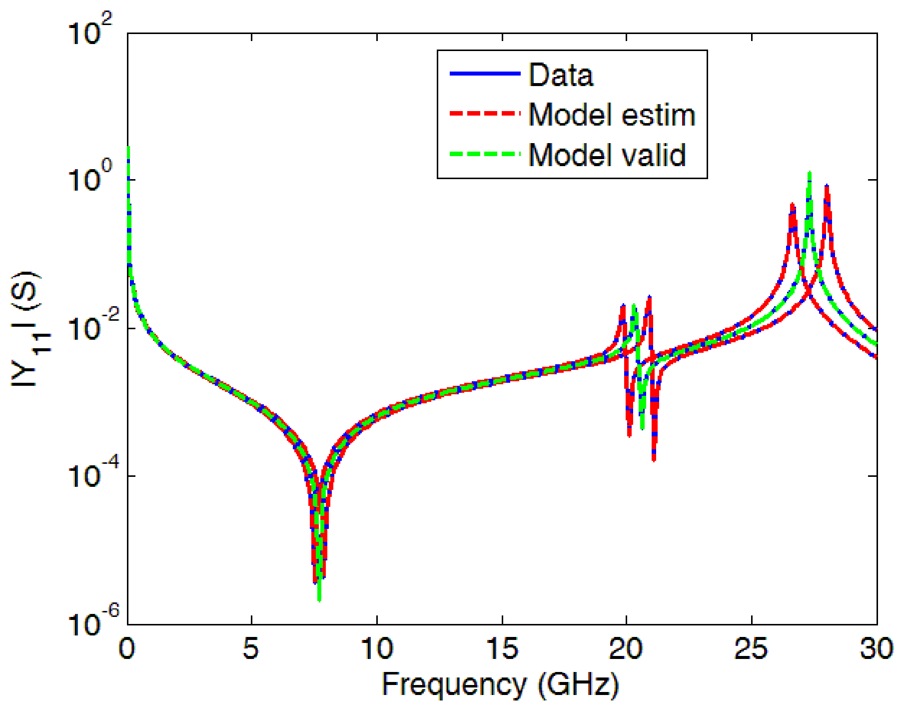
Lx = [0.57,0.60,0.63] mm, Ly = 0.57 mm





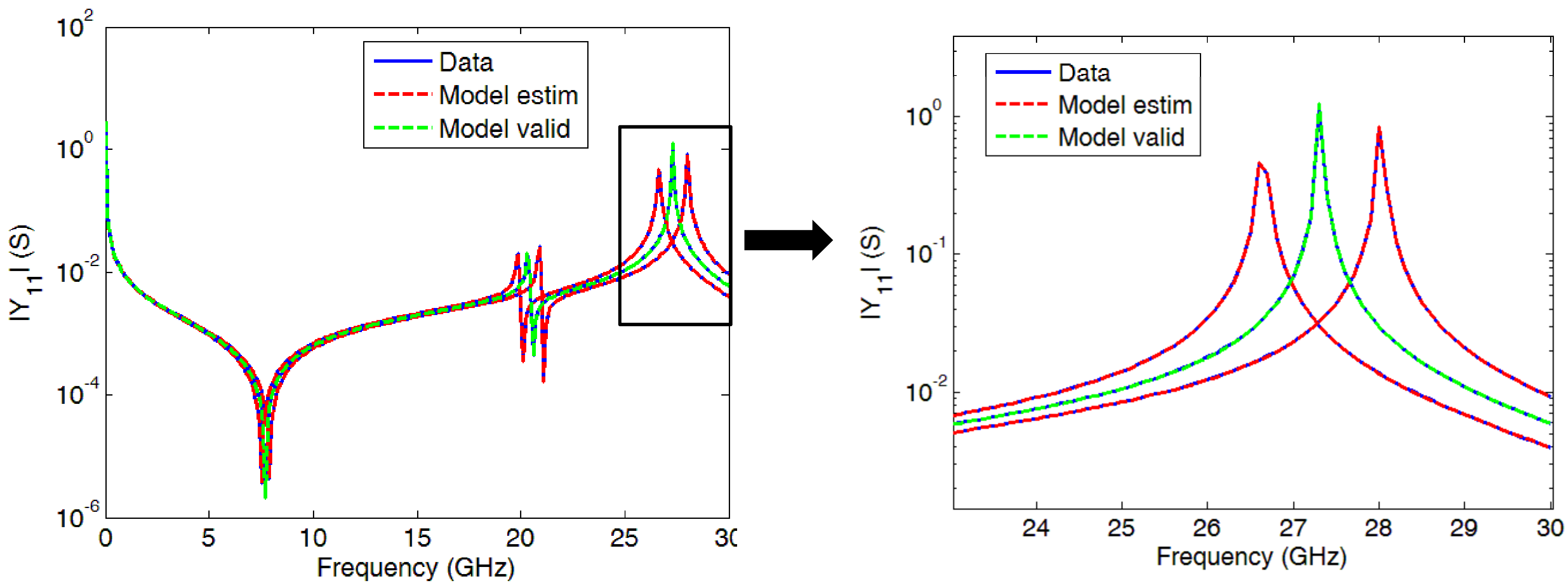
3D example: Spiral inductor (With scaling-shifting coefficients)

Lx = [0.57,0.60,0.63] mm, Ly = 0.57 mm



3D example: Spiral inductor (With scaling-shifting coefficients)

Lx = [0.57,0.60,0.63] mm, Ly = 0.57 mm



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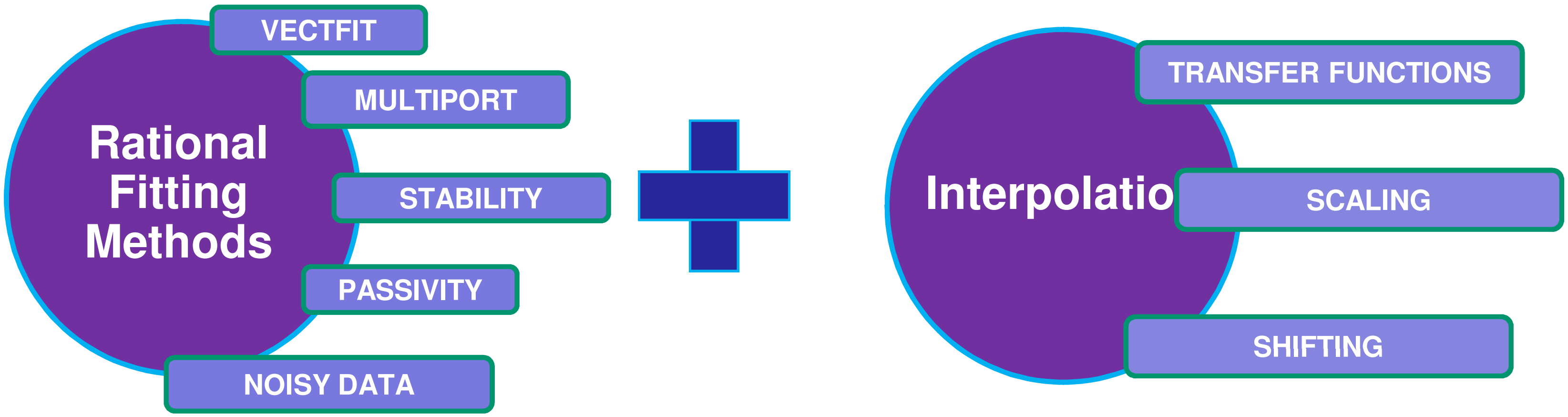
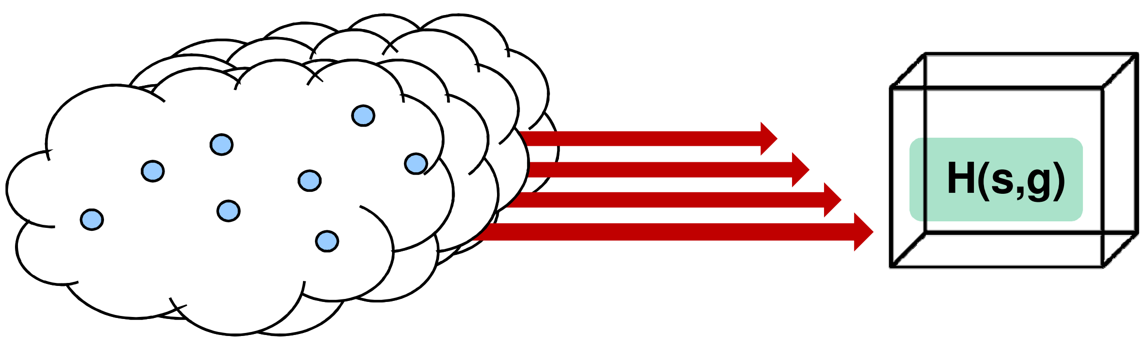


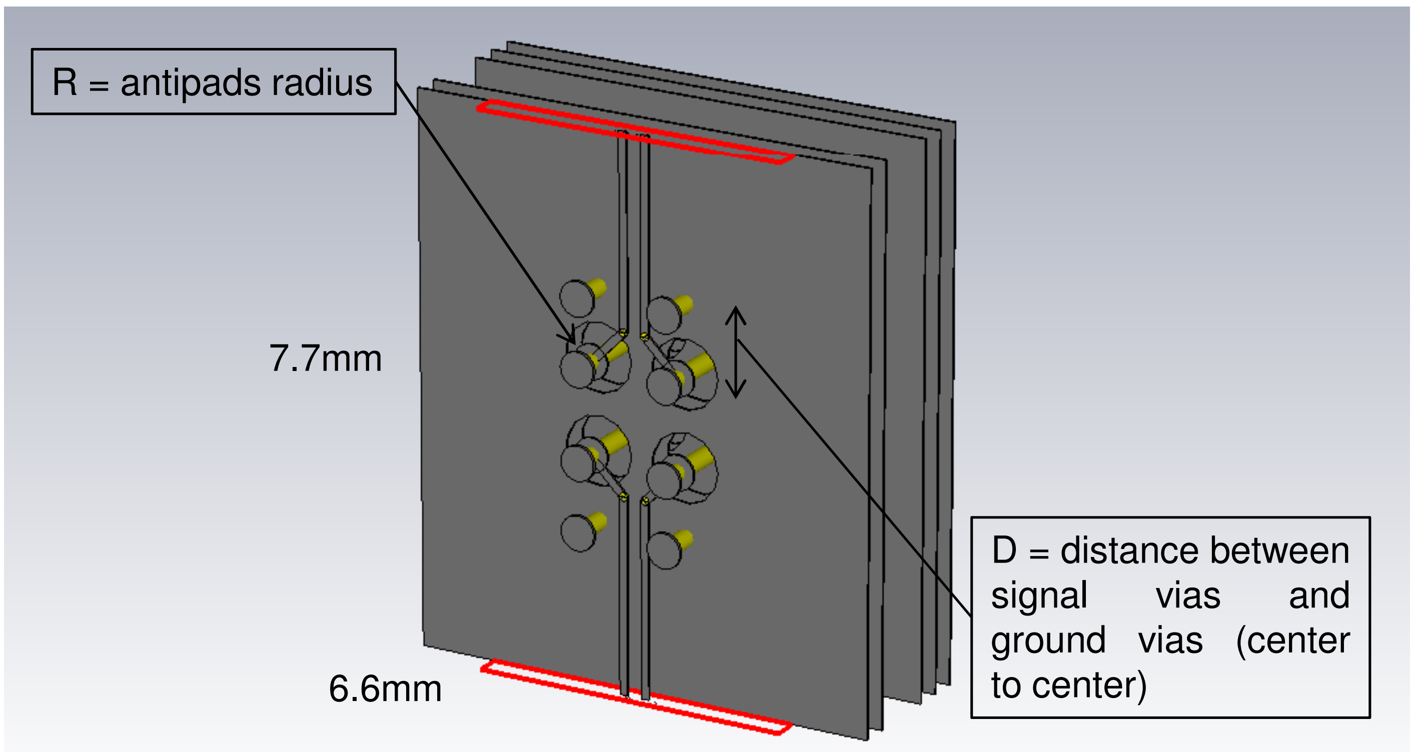
data-driven PMOR



scattered data

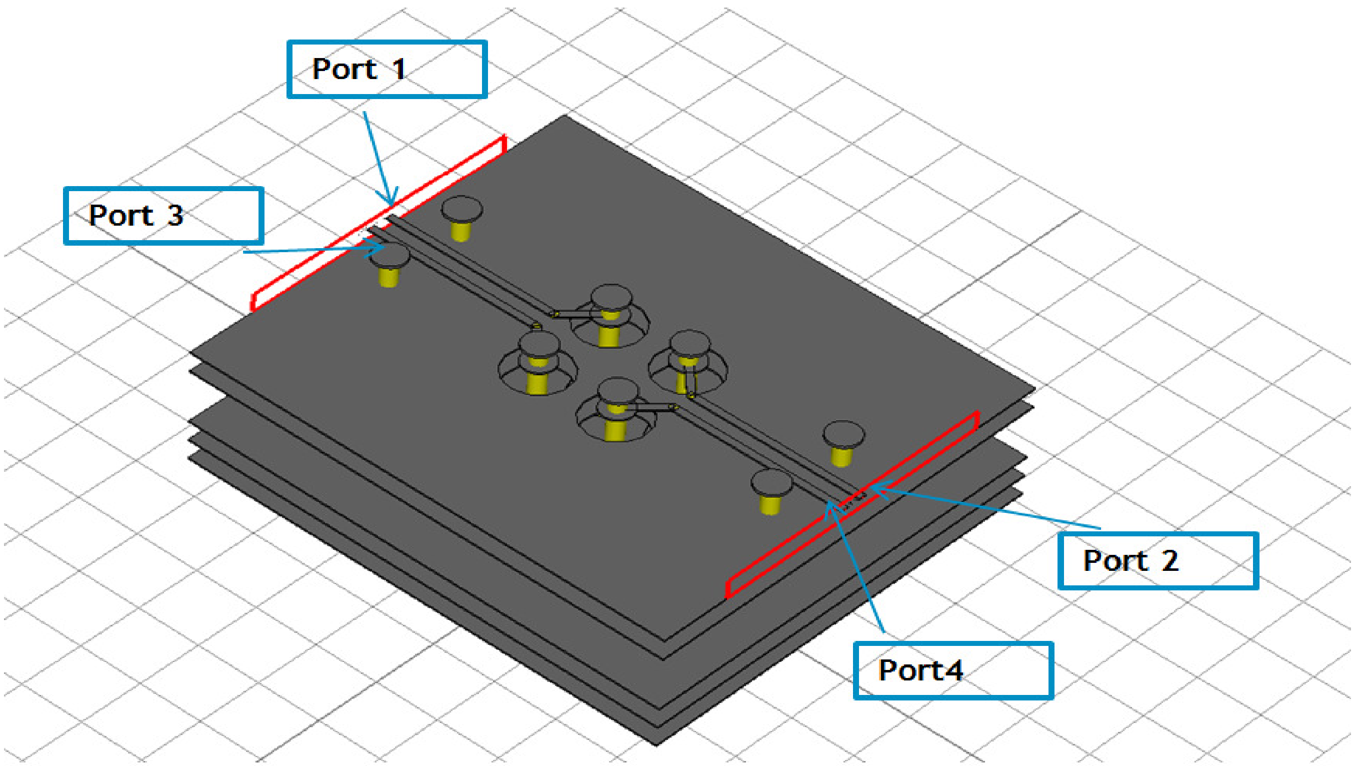
3D example: PCB

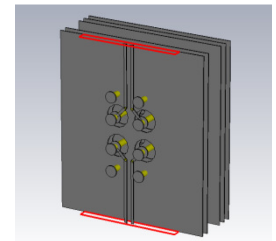
Parameter	Min	Max
Frequency (freq)	0 Hz	20 GHz
Antipads radius (R)	0.4826 mm	0.6026 mm
Distance (D)	1.2525 mm	2.4525 mm



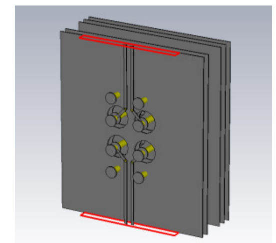
3D example: PCB

Parameter	Min	Max
Frequency (freq)	0 Hz	20 GHz
Antipads radius (R)	0.4826 mm	0.6026 mm
Distance (D)	1.2525 mm	2.4525 mm





Step	CPU time
Estimation grid by solver (4×6) (R,D)	3 h 6 min
Validation grid by solver (3×5) (R,D)	1 h 56 min 15 s
Building model	5 min 49 s
Validating model	11 s
Evaluating solver (one frequency response)	7 min 45 s
Evaluating model (one frequency response)	0.1 s



Step	CPU time
Estimation grid by solver (4×6) (R,D)	3 h 6 min
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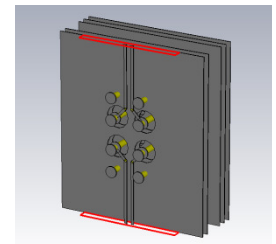
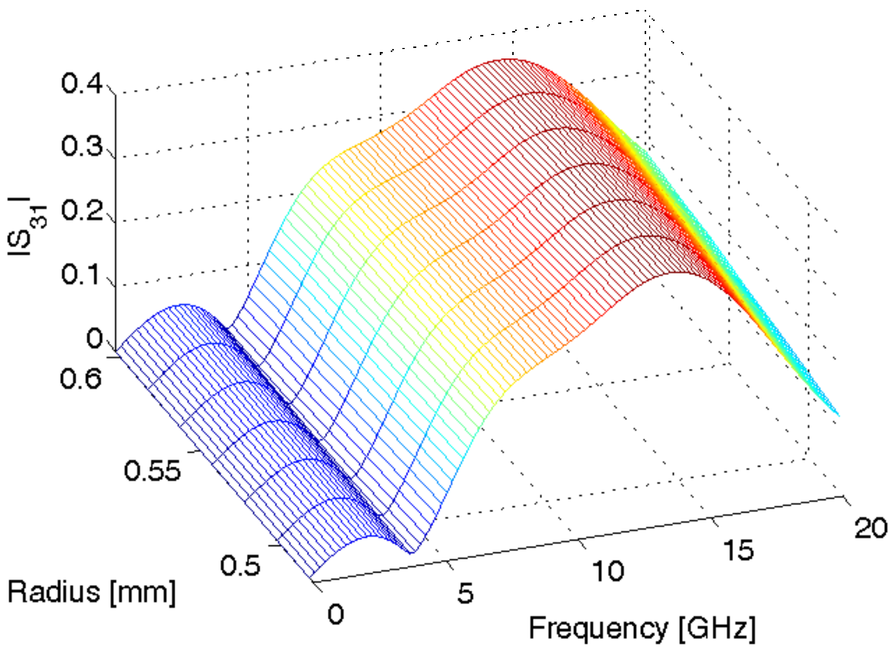
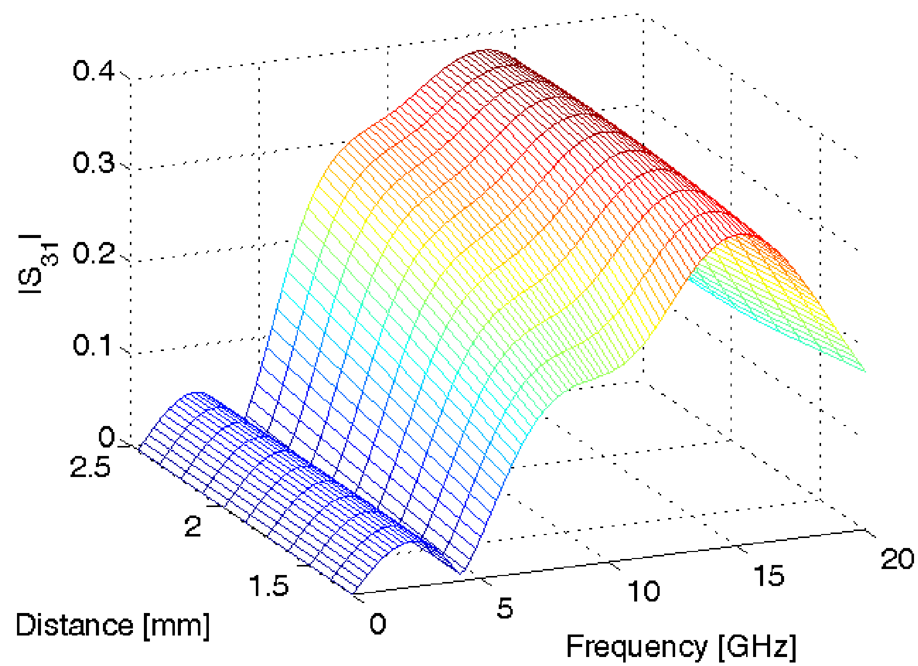
Speed-up 4650 x

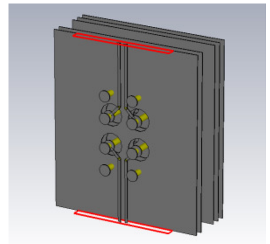


D=1.8525 mm



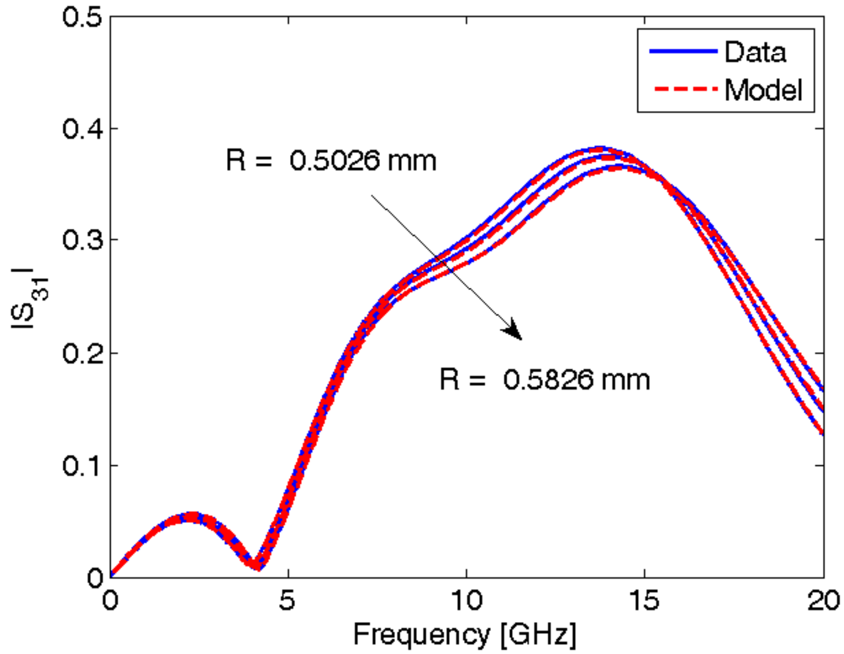
R=0.543 mm

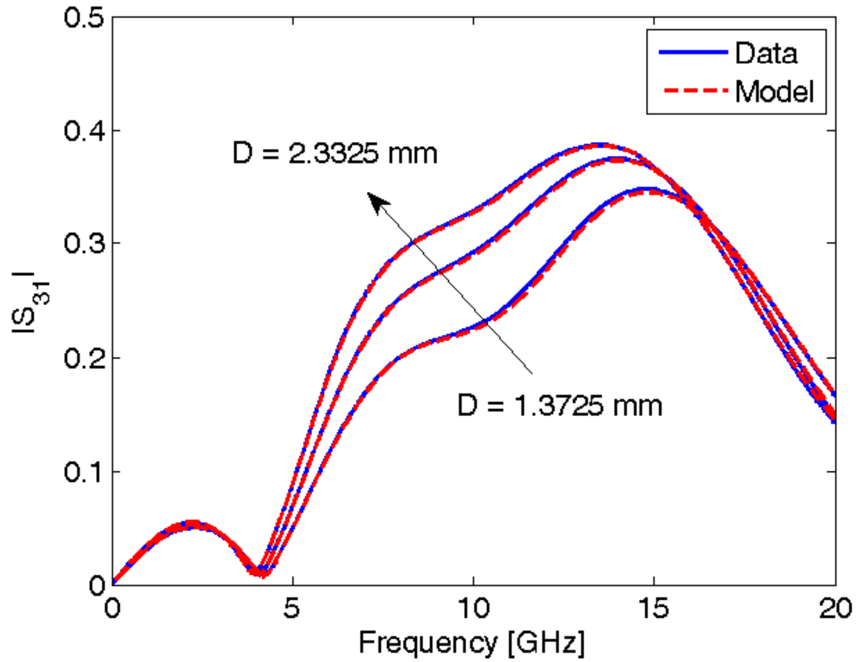


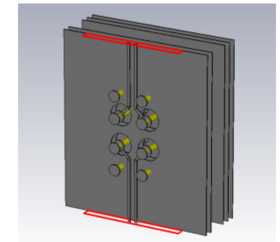


D=1.8525 mm

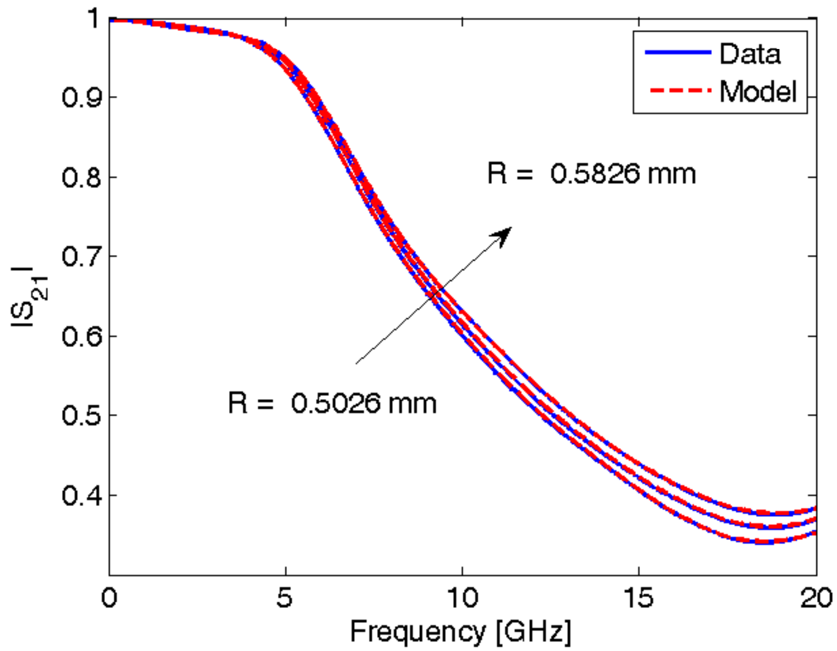
R=0.543 mm



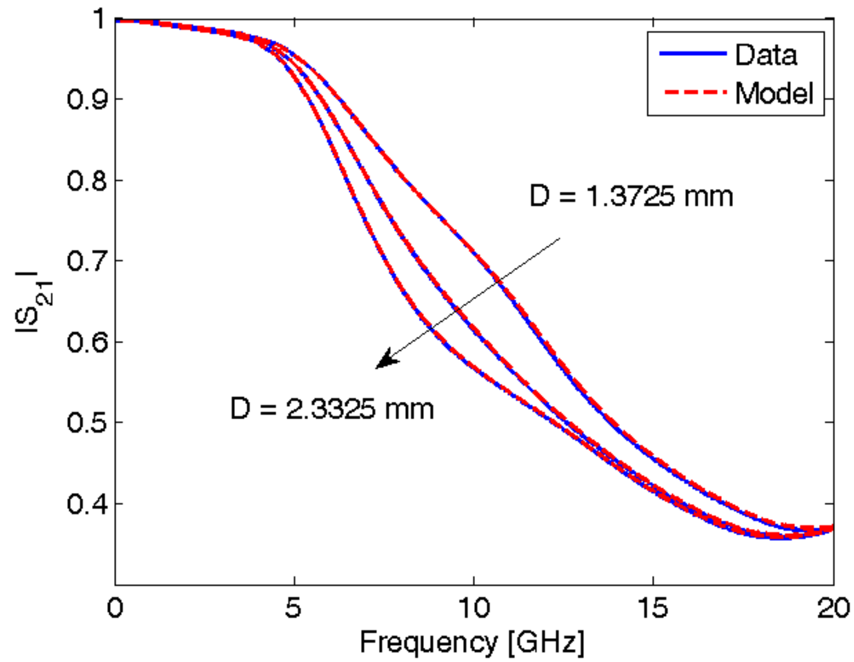




D=1.8525 mm



R=0.543 mm



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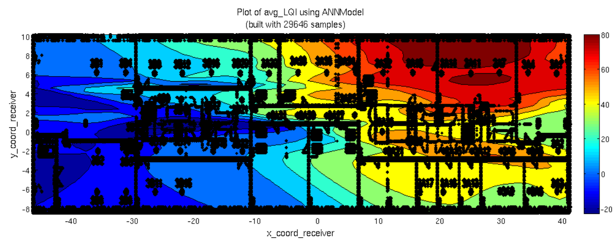
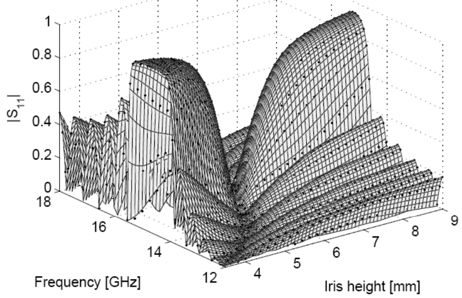
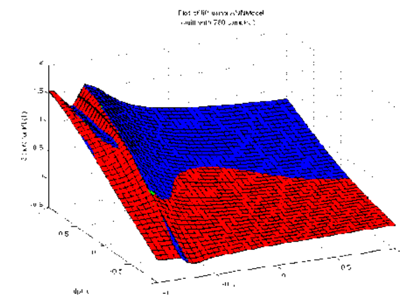


electronics



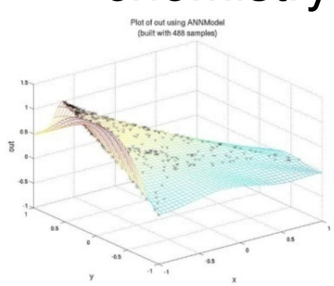
fluid dynamics



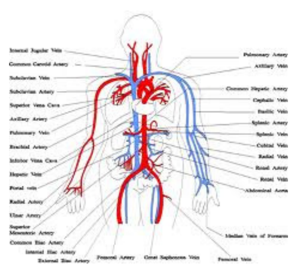
input → out = f(*in*) → output

automotive

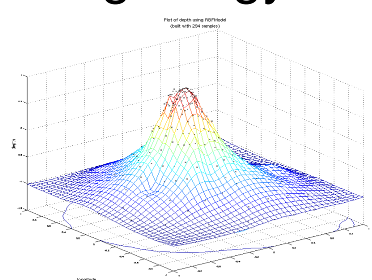
chemistry

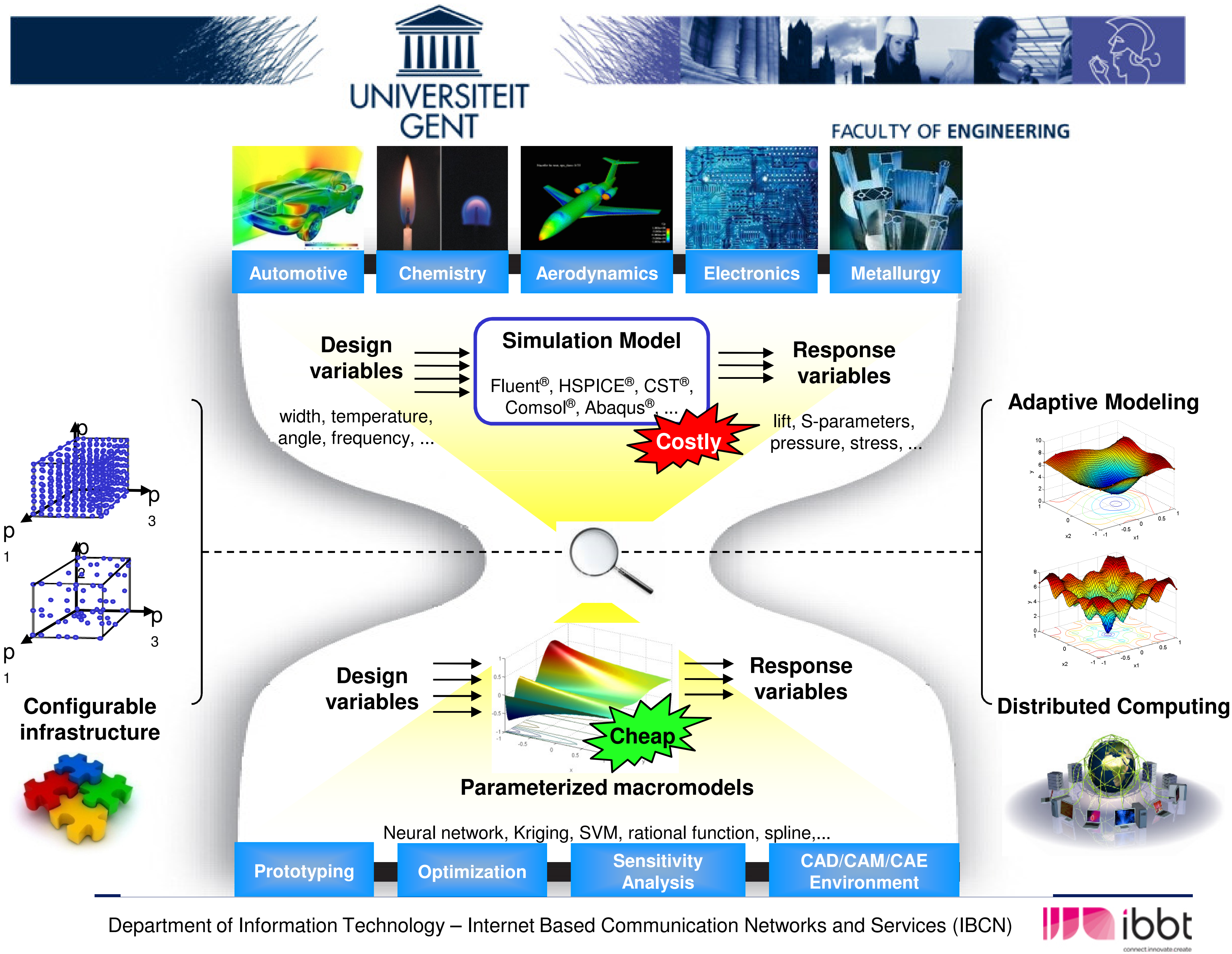


biomodeling



geology

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Automotive
Chemistry
Aerodynamics
Electronics
Metallurgy
Design variables
Simulation Model
Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...
Response variables
width, temperature, angle, frequency, ...
Costly
lift, S-parameters, pressure, stress, ...
Adaptive Modeling
Configurable infrastructure
Design variables
Response variables
Cheap
Parameterized macromodels
Distributed Computing
Neural network, Kriging, SVM, rational function, spline,...
Prototyping
Optimization
Sensitivity Analysis
CAD/CAM/CAE Environment
Department of Information Technology – Internet Based Communication Networks and Services (IBCN)
ibbt
connect.innovate.create

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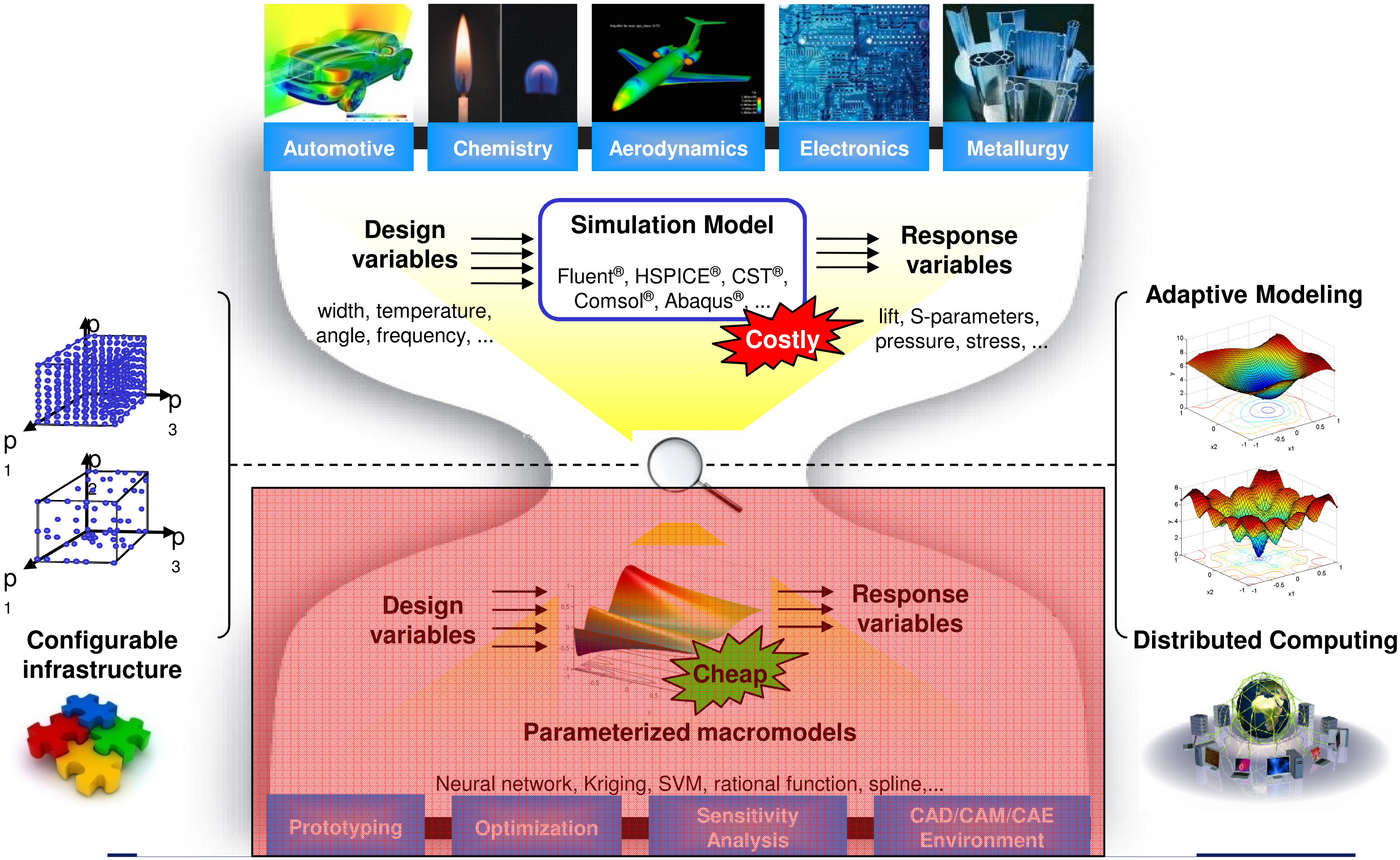
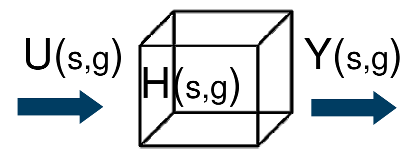


ibbt
connect.innovate.create

Parameterized macromodels



parameterized macromodel

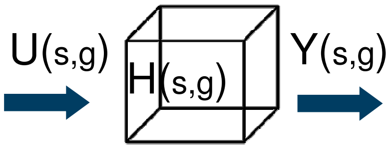
Multiple design variables

Compact models

Efficient design activities (excellent speed-ups)

- **Multiple simulations (measurements)**
  - **Design space optimization, exploration, sensitivity analysis**

Parameterized macromodels



parameterized macromodel

Time-domain simulations
- **Non-linear drivers and receivers**

Stochastic modeling
- **impact of manufacturing tolerances**

High number of dimensions

Models from measurements
- **noise to handle**

Applications in different domains

Questions

Contact info: francesco.ferranti@ugent.be

Recent publications

F. Ferranti, L. Knockaert, T. Dhaene, "Passivity-Preserving Parametric Macromodeling by Means of Scaled and Shifted State-Space Systems", IEEE Trans. on Microwave Theory and Techniques, vol. 59, no. 10, pp.2394-2403, October 2011.

F. Ferranti, T. Dhaene, L. Knockaert, G. Antonini and A. Ciccomancini Scogna, "Scalable Compact Models for Fast Design Optimization of Complex Electromagnetic Systems", International Journal of RF and Microwave Computer-Aided Engineering, vol. 22, no. 1, pp. 20-29, January 2012.

F. Ferranti, M. Nakhla, G. Antonini, T. Dhaene, L. Knockaert, A. E. Ruehli, “Interpolation-based Parameterized Model Order Reduction of Delayed Systems”, IEEE Trans. on Microwave Theory and Techniques, vol. 60, no. 3, pp. 431-440, March 2012.

Contact info: francesco.ferranti@ugent.be